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THE CAUSE, DEVELOPMENT AND OUTCOME  
OF WORD-OF-MOUTH MARKETING: WITH  
PARTICULAR REFERENCE TO WOM VOLUME,  
VALENCE AND THE MODELING OF VIRAL  
MARKETING

**Ying WU**

**PhD Thesis**

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‘I hereby declare that this thesis has not been and will not be, submitted in whole or in part to another University for the award of any other degree.’

Signature.....

### **Abstract**

Viral marketing is a form of online word-of-mouth (WOM) communication in which individuals are encouraged to pass on promotional messages through social websites. With the growing popularity of online social websites, viral marketing has increasingly garnered attention of marketers and marketing researchers alike. The two most important WOM attributes highlighted in the extant literature are volume and valence. This thesis looked into the cause, development and outcome of WOM marketing and provided computational models for forecasting the development of WOM volume and valence of viral marketing in social websites. With the data extracted from large-scale web-crawling activities, through a series of computer simulation experiments comparable to social websites, the author developed models to predict WOM volume and valence in viral marketing. The model for predicting WOM volume in viral marketing used theories of network topologies. The model for predicting WOM valence in viral marketing used an artificial neural network model. The author discussed the insights from the findings and suggested viral marketing strategies to optimize the performance of WOM volume and valence in social websites. A key contribution of this thesis is the new approaches of modeling and data collection for WOM volume and valence forecasting in viral marketing.



## **Table of Contents**

|                   |            |
|-------------------|------------|
| TITLE PAGE        | <b>1</b>   |
| ACKNOWLEDGEMENTS  | <b>2</b>   |
| ABSTRACT          | <b>3</b>   |
| TABLE OF CONTENTS | <b>4</b>   |
| LIST OF TABLES    | <b>12</b>  |
| LIST OF FIGURES   | <b>15</b>  |
| BIBLIOGRAPHY      | <b>332</b> |

## **CHAPTER ONE**

### **INTRODUCTION AND BACKGROUND**

|  |    |
|--|----|
| 1.1 INTRODUCTION   | 20 |
| 1.1.1 WOM VOLUME   | 24 |
| 1.1.2 WOM VALENCE  | 26 |
| 1.1.3 BACKGROUND – THE SIGNIFICANCE OF VIRAL<br>MARKETING AND ITS DEFINITION | 28 |
| 1.2 RATIONALE FOR THIS STUDY   | 34 |
| 1.3 DISTINGUISHING WOM AND EWOM  | 39 |
| 1.4 AIMS AND SCOPE OF THE STUDY  | 40 |
| 1.5 OVERVIEW OF THE THESIS   | 44 |

## **CHAPTER TWO**

### **LITERATURE REVIEW**

|  |    |
|--|----|
| 2.1 WOM AND VIRAL MARKETING: AN<br>INTRODUCTORY OVERVIEW | 46 |
|--|----|

|  |    |
|--|----|
| 2.1.1 INTRODUCING WOM AND VIRAL MARKETING  | 46 |
| 2.1.2 THE EFFECTIVENESS OF WOM AND VIRAL<br>MARKETING  | 53 |
| 2.1.3 THE RIPPLE EFFECT OF WOM   | 58 |
| 2.1.4 THE DIFFERENCES BETWEEN ONLINE WOM<br>AND OFFLINE WOM  | 61 |
| 2.1.5 PREVIOUS RESEARCH ON THEORETICAL<br>FRAMEWORKS AND MATHEMATICAL MODELING OF<br>WOM AND EWOM                      | 74 |
| 2.1.5.1 THE ORGANIC INTERCONSUMER INFLUENCE<br>MODEL   | 75 |
| 2.1.5.2 THE LINEAR MARKETER INFLUENCE MODEL<br>AND TREE TOPOLOGY MODEL   | 77 |
| 2.1.5.3 THE NETWORK COPRODUCTION MODEL AND<br>COMPLEX NETWORK TOPOLOGY MODEL   | 83 |
| 2.2 THE CAUSE, DEVELOPMENT AND OUTCOME OF<br>WOM MARKETING: WITH PARTICULAR REFERENCE<br>TO THE MODELING OF WOM VOLUME | 86 |

|   |            |
|---|------------|
| 2.2.1. THE CAUSE OF WOM VOLUME  | <b>86</b>  |
| 2.2.2 NETWORK TOPOLOGY AND THE DEVELOPMENT<br>OF WOM VOLUME   | <b>92</b>  |
| 2.2.2.1 NETWORK TOPOLOGY THEORY AS<br>CONCEPTUAL BASE FOR WOM VOLUME  | <b>93</b>  |
| 2.2.2.2 NETWORK TOPOLOGIES AND WOM VOLUME<br>DEVELOPMENT  | <b>106</b> |
| 2.2.2.2.1 NETWORK TOPOLOGIES SELECTION  | <b>106</b> |
| 2.2.2.2.2 DEFINING VARIABLES  | <b>127</b> |
| 2.2.3 THE OUTCOME OF WOM VOLUME   | <b>132</b> |
| 2.3 THE CAUSE, DEVELOPMENT AND OUTCOME OF<br>WOM MARKETING: WITH PARTICULAR REFERENCE<br>TO THE MODELING OF WOM VALENCE | <b>134</b> |
| 2.3.1 OVERVIEW OF PREVIOUS LITERATURE<br>REGARDING THE CAUSE OF WORD-OF-MOUTH<br>VALENCE                                | <b>134</b> |
| 2.3.2 ARTIFICIAL NEURAL NETWORKS AND THE<br>DEVELOPMENT OF WOM VALENCE  | <b>152</b> |

|  |     |
|--|-----|
| 2.3.2.1 A REVIEW OF ARTIFICIAL NEURAL NETWORKS                                       | 152 |
| 2.3.2.2 ANN SELECTION  | 159 |
| 2.3.2.3 DEFINING VARIABLES   | 167 |
| 2.3.3 THE OUTCOME OF WOM VALENCE   | 168 |
| 2.4 VARIABLES FOR THE MODELING OF WOM VOLUME AND WOM VALENCE                         | 178 |
| 2.4.1 VARIABLES IN THE MATHEMATICAL EXPRESSIONS OF WOM VOLUME                        | 178 |
| 2.4.2 VARIABLES FOR THE MODELING OF WOM VALENCE                                      | 180 |
| 2.4.3 SUCCESSFUL VIRAL MARKETING CAMPAIGNS: HIGH WOM VOLUME AND POSITIVE WOM VALENCE | 180 |
| 2.5 CHAPTER SUMMARY  | 187 |

## **CHAPTER THREE**

### **RESEARCH OBJECTIVES AND METHODOLOGY**

|  |            |
|--|------------|
| 3.1 INTRODUCTION   | <b>189</b> |
| 3.2 PHILOSOPHICAL POSITIONING  | <b>191</b> |
| 3.3 RESEARCH METHODOLOGY   | <b>192</b> |
| 3.3.1 ESTIMATION OF DYNAMIC WOM VOLUME<br>DEVELOPMENT USING NETWORK TOPOLOGY<br>MODELS           | <b>192</b> |
| 3.3.1.1 INTRODUCTION OF COMPLEX NETWORKS   | <b>192</b> |
| 3.3.1.2 SMALL WORLD NETWORKS   | <b>199</b> |
| 3.3.1.3 RANDOM NETWORKS  | <b>204</b> |
| 3.3.1.4 SCALE-FREE NETWORKS  | <b>205</b> |
| 3.3.2 ESTIMATION OF DYNAMIC WOM VALENCE<br>DEVELOPMENT USING ARTIFICIAL NEURAL<br>NETWORK MODELS | <b>208</b> |
| 3.3.3 SAMPLING METHODS AND DATA SOURCING   | <b>225</b> |

|                                       |     |
|---------------------------------------|-----|
| 3.3.4 EXPERIMENTAL DESIGN             | 243 |
| 3.3.5 COMPUTER SIMULATION EXPERIMENTS | 251 |
| 3.4 CHAPTER SUMMARY                   | 281 |

## **CHAPTER FOUR**

### **DATA ANALYSIS AND DISCUSSION**

|  |     |
|--|-----|
| 4.1 DATA ANALYSIS AND DISCUSSION OF WOM<br>VOLUME  | 282 |
| 4.2 DATA ANALYSIS AND DISCUSSION OF WOM<br>VALENCE | 305 |
| 4.3 CHAPTER SUMMARY                                | 316 |

## **CHAPTER FIVE**

### **CONCLUSION**

|                                     |     |
|-------------------------------------|-----|
| 5.1 MAIN CONTRIBUTIONS OF THE STUDY | 317 |
| 5.1.1 KEY FINDINGS FROM THE STUDY   | 317 |

|  |            |
|--|------------|
| 5.1.2 KEY THEORETICAL CONTRIBUTIONS                    | <b>325</b> |
| 5.1.3 KEY PRACTICAL CONTRIBUTIONS                      | <b>327</b> |
| 5.1.4 KEY EMPIRICAL CONTRIBUTIONS                      | <b>327</b> |
| 5.2 MANAGERIAL IMPLICATIONS                            | <b>329</b> |
| 5.3 LIMITATIONS AND SUGGESTIONS FOR FUTURE<br>RESEARCH | <b>330</b> |



## **LIST OF TABLES**

TABLE 1 PREVIOUS LITERATURE ON WOM

TABLE 2 DIMENSIONAL DIFFERENCES BETWEEN WOM AND  
EWOM

TABLE 3 THE COMPARISON OF EMPIRICAL STUDIES ON THE  
EFFECTIVENESS OF WOM

TABLE 4 ONLINE WOM AND OFFLINE WOM

TABLE 5 SUMMARY OF PREVIOUS RESEARCH ON EWOM

TABLE 6 MOTIVATIONS OF WOM

TABLE 7 A COMPARISON OF SIMPLE NETWORK TOPOLOGIES

TABLE 8 VARIABLES OF THE WOM VOLUME MODEL

TABLE 9 INPUT VARIABLES DEFINED FOR THE MODELING OF  
WOM VALENCE

TABLE 10 EFFECTS OF WOM

TABLE 11 VARIABLES FOR THE MODELING OF WOM VOLUME

TABLE 12 VARIABLES FOR THE MODELING OF WOM VALENCE

TABLE 13 MAIN OBJECTIVES AND METHODOLOGIES

TABLE 14 COMPLEX SYSTEMS THAT HAVE BEEN STUDIED

TABLE 15 COMPLEX NETWORKS

TABLE 16 INPUT STIMULI FOR ANN

TABLE 17 DATA SOURCING: TWITTER AND WEIBO (CHINA'S  
VERSION OF TWITTER)

TABLE 18 EXAMPLES OF TWITTER API

TABLE 19 AN EXAMPLE OF REALIZATION OF THE COMPLEX  
NETWORK TOPOLOGY MODEL WITH ONE SEEDING SOURCE

TABLE 20 A NETWORK TOPOLOGY OVERVIEW OF KATY PERRY'S  
TWEET

TABLE 21 A NETWORK TOPOLOGY OVERVIEW OF XIAOMI WEIBO  
VOLUME DEVELOPMENT

TABLE 22 VARIABLES FOR THE MODELING OF ONLINE WOM  
VOLUME

TABLE 23 DATA FITTING PERFORMANCE OF TREE TOPOLOGY  
MODELS

TABLE 24 PARAMETER ESTIMATES FOR TREE TOPOLOGY MODEL

TABLE 25 DATA FITTING PERFORMANCE OF SCALE FREE MODELS

TABLE 26 PARAMETER ESTIMATES FOR SCALE FREE MODEL

TABLE 27 DATA FITTING PERFORMANCE OF RANDOM NETWORK  
TOPOLOGY WOM VOLUME MODEL

TABLE 28 PARAMETER ESTIMATES FOR RANDOM NETWORK  
TOPOLOGY MODEL

TABLE 29 DATA FITTING PERFORMANCE OF SMALL WORLD  
NETWORK TOPOLOGY WOM VOLUME MODEL

TABLE 30 PARAMETER ESTIMATES FOR SMALL WORLD NETWORK  
TOPOLOGY MODEL

TABLE 31 TOPOLOGY WOM VOLUME MODELS DISPLAYED GOOD  
FIT IN COMPUTER SIMULATION

TABLE 32 WOM VALENCE OVERVIEW OF KATY PERRY’S TWEET

TABLE 33 WOM VALENCE EXAMPLES FROM KATY PERRY’S  
TWEET

TABLE 34 WOM VALENCE OVERVIEW OF XIAOMI WEIBO

TABLE 35 WOM VALENCE EXAMPLES FROM XIAOMI WEIBO

TABLE 36 THE SIX INPUT LAYER NODES OF THE ANN MODEL FOR  
WOM VALENCE PREDICTIVE MODELING

TABLE 37 TWITTER DATA FITTING –WOM VALENCE

TABLE 38 THE VARIABLES USED FOR THE MODELING OF WOM  
VOLUME

TABLE 39 THE INPUT VARIABLES USED FOR THE MODELING OF  
WOM VALENCE

## **LIST OF FIGURES**

FIGURE 1 WOM AND VIRAL MARKETING

FIGURE 2 ELABORATION LIKELIHOOD MODEL (ELM) (KENRICK,  
NEUBERG, AND CIALDINI, 2002)

FIGURE 3 THE RIPPLE EFFECT OF WOM

FIGURE 4 THE ORGANIC INTERCONSUMER INFLUENCE MODEL

FIGURE 5 THE LINEAR MARKETER INFLUENCE MODEL

FIGURE 6 SPREAD OF A MESSAGE IN A VIRAL MARKETING  
CAMPAIGN AS A BRANCHING PROCESS

FIGURE 7 BRANCHING PROCESS BY VAN DER LANS (2010)

FIGURE 8 THE NETWORK COPRODUCTION MODEL

FIGURE 9 BRANCHING PROCESS

FIGURE 10 VISUALIZATION OF AN EXAMPLE RETWEET NETWORK  
EMERGENT FROM THE MESSAGE PROPAGATION ON THE  
FOLLOWERS NETWORK

FIGURE 11 PREVIOUS RESEARCH ON SOCIAL NETWORK  
TOPOLOGY STUDIES

FIGURE 12 NETWORK TOPOLOGIES

FIGURE 13 BUS TOPOLOGY

FIGURE 14 STAR TOPOLOGY

FIGURE 15 RING TOPOLOGY

FIGURE 16 TREE TOPOLOGY

FIGURE 17 FULL MESH

FIGURE 18 PARTIAL MESH

FIGURE 19 AN EWOM VOLUME DEVELOPMENT PROCESS FROM A  
PARTICIPANT'S PERSPECTIVE (TWITTER)

FIGURE 20 AN EWOM VOLUME DEVELOPMENT PROCESS FROM A  
PARTICIPANT'S PERSPECTIVE(WEIBO)

FIGURE 21 NONLINEAR DYNAMIC ANN

FIGURE 22 LINEAR THRESHOLD FUNCTION

FIGURE 23 MCCULLOCH PITTS NEURON MODEL

FIGURE 24 ADALINE NEURON MODEL

FIGURE 25 BACK PROPAGATION NEURAL NETWORK MODEL

FIGURE 26 EWOM ACTIVITIES

FIGURE 27 EFFECTS OF WOM VALENCE

FIGURE 28 HIGH WOM VOLUME AND POSITIVE WOM VALENCE

FIGURE 29 TOPOLOGIES FEATURES

FIGURE 30 SMALL WORLD NETWORKS

FIGURE 31 SMALL WORLD NETWORKS (CONTINUED.)

FIGURE 32 RANDOM NETWORKS

FIGURE 33 SCALE FREE NETWORKS

FIGURE 34 STRUCTURE OF BIOLOGICAL NEURON

FIGURE 35 STRUCTURE OF ANN

FIGURE 36 OUTSTAR ARCHITECTURE. SQUARES DENOTE NODES.  
SEMICIRCLES DENOTE MODIFIABLE EXCITATORY CONNECTIONS.

FIGURE 37 THE CS-US NEURON

FIGURE 38 SCHEME OF MULTI-LAYER PERCEPTRON NEURAL  
NETWORK

FIGURE 39 WEB CRAWLING

FIGURE 40 DIAGRAM OF THE TWITTER DATA COLLECTING TOOL

FIGURE 41 FLOW OF TOPOLOGY EXTRACTION

FIGURE 41 ONE TWITTER POST USED FOR WEB CRAWLING ON  
TWITTER

FIGURE 42 COMPUTER SIMULATION EXPERIMENT

FIGURE 43 THE SIMULATION EXPERIMENT PROCESS

FIGURE 44 AN EWOM VOLUME DEVELOPMENT PROCESS FROM A  
PARTICIPANT'S PERSPECTIVE (TWITTER)

FIGURE 45 AN EWOM VOLUME DEVELOPMENT PROCESS FROM A  
PARTICIPANT'S PERSPECTIVE (WEIBO)

FIGURE 46 AN EXAMPLE OF EWOM VOLUME DEVELOPMENT  
PROCESS IN A COMPLEX NETWORK ILLUSTRATING SOME OF THE  
VARIABLES

FIGURE 47 NVIVO SCREENSHOT OF CODING THE INPUT NODES OF  
THE ANN MODEL (TWITTER)

FIGURE 48 NVIVO SCREENSHOT OF CODING THE INPUT NODES OF  
THE ANN MODEL (WEIBO)

FIGURE 49 ANN MODELING PLATFORM MATLAB

FIGURE 50 ONE TWITTER POST USED FOR WEB CRAWLING ON  
TWITTER

FIGURE 51 ONE WEIBO POST USED FOR WEB CRAWLING

FIGURE 52 TREES TOPOLOGY (CUMULATIVE NUMBER OF WOM  
VOLUME IN THE OVERALL NETWORKS - (A) INCLUDES 11,207  
NODES (B) 1,291,352 NODES)

FIGURE 53 SCALE FREE TOPOLOGY

FIGURE 54 SCALE-FREE (CUMULATIVE NUMBER OF WOM  
VOLUME IN THE OVERALL NETWORKS - (A) INCLUDES 11,207  
NODES (B) 1,291,352 NODES)

FIGURE 55 RANDOM NETWORK TOPOLOGY

FIGURE 56 RANDOM (CUMULATIVE NUMBER OF WOM VOLUME IN  
THE OVERALL NETWORKS - (A) INCLUDES 11,207 NODES (B)  
1,291,352 NODES)

FIGURE 57 SMALL WORLD TOPOLOGY

FIGURE 58 SMALL WORLD (CUMULATIVE NUMBER OF WOM  
VOLUME IN THE OVERALL NETWORKS - (A) INCLUDES 11,207  
NODES (B) 1,291,352 NODES)

FIGURE 59 NVIVO SCREENSHOT OF QUALITATIVE DATA  
ANALYSIS (TWITTER)

FIGURE 60 NVIVO SCREENSHOT OF QUALITATIVE DATA  
ANALYSIS (WEIBO)

FIGURE 61 TWITTER VALENCE DATA FITTING

FIGURE 62 WEIBO VALENCE DATA FITTING



## **CHAPTER ONE**

### **INTRODUCTION AND BACKGROUND**

#### **1.1 INTRODUCTION**

The term "word of mouth" (WOM) commonly refers to the flow of communications among consumers about products and services (Westbrook 1987). Nowadays in world that offers a plethora of product information from a wealth of sources (Plummer, 2007), with a phenomenon that modern consumers have become less attentive to traditional advertising (Nail 2005, Nielsen, 2007, Verlegh and Moldovan 2008), consumer evaluations and opinions of a product or service have become widely available and WOM plays an even more important role today in shaping consumers' attitudes and buying behaviors.

Word-of-mouth (WOM) represents one of the most influential sources of information transfer by consumers (Duan, Gu, and Whinston 2008; Swan and Oliver 1989; Maxham and Netemeyer 2002; Reynolds and Beatty 1999), with well-documented benefits (Godes et al. 2005; Hoch and Ha 1986). WOM has been frequently cited as one of the most powerful forces in the marketplace

(e.g. Trusov et al., 2009; Schmitt et al., 2011). This finding dates back to Katz and Lazarsfeld's seminal study in the 1940s, which found that word-of-mouth is at least twice as influential as the mass media (Katz and Lazarsfeld, 1955, Engel et al. 1969, Herr et al., 1991). Consumers tend to be influenced by their social interactions with others when they make purchase decisions (Godes et al. 2005). They often rely on others for assistance with purchases, especially for products with high financial or psychic risk (Gershoff and Johar 2006). According to the Keller Fay Group (2006), 3.4 billion conversations about brands take place everyday. Based on the 2007 Nielsen Global Survey, 78% of people found "recommendations from consumers" being the form of advertising that they trust most. Some practitioners even argue that one single survey question can serve as a useful predictor of growth-that is, whether your customers are willing to recommend a product to others (Reichheld 2003). Social talk generates more than 3.3 billion brand impressions each day (Keller and Libai 2009), are considered the primary driving force in two-thirds of all industries (Dye 2000). WOM has been shown to affect purchasing behavior regarding everything from the products consumers buy to the drugs physicians prescribe (Godes and Mayzlin 2009; Iyengar, Van den Bulte, and Valente 2009; Leskovec, Adamic, and Huberman 2007; Moe and Trusov 2011).

Firms are gaining increasing capacity to initiate and manage consumer social interactions directly (Godes et al. 2005), tasks either impossible or too costly

in the past. For example, the Internet, e-commerce, and information technology have created opportunities for firms to effectively facilitate WOM communication by allowing buyers to post consumer reviews based on their personal experiences on firms' Websites or licensing consumer reviews from third-party sites, such as Epinions.com (Chen and Xie 2008). According to Kilby (2007), many organisations have reduced expenditures on traditional advertising and re-visited WOM as a powerful marketing tool.

The two most important WOM attributes studied in the literature are volume (i.e., the amount of WOM information; e.g., Anderson 1998; Bowman and Narayandas 2001) and valence (i.e., whether the opinions from WOM are positive or negative; e.g., Herr, Kardes, and Kim 1991). Previous research has indicated that WOM valence can influence product sales by changing consumer valuation of the products (e.g., Chevalier and Mayzlin 2006; Mizerski 1982), and WOM volume plays an informative role by increasing the degree of consumer awareness and the number of informed consumers in the market (Liu, 2006). A plethora of popular books on WOM Marketing have recently been released (e.g., Jaffe 2007; Kelly 2007; Rosen 2009; Sernovitz 2006), and industry associations, such as the Word of Mouth Marketing Association, have grown rapidly and have advocated for the burgeoning new industry.

The use of network topologies as a mean to present order and arrangement of social contacts within a population has a long history in social science. In the 1930s, network topologies theory was first introduced as the idea of using a graph or network structure to represent relationships between individuals and/or groups. It has subsequently been developed over time by a variety of workers into a coherent field of study known as social network analysis (Wasserman and Faust, 1994; Scott, 2000; Rhodes and Keefe, 2007).

At the simplest level, social networks are represented by a number of nodes that corresponds to individuals or groups, which are connected by a number of links that correspond to certain forms of connection or tie between individuals or groups. Network structures are appealing to study because they immediately reveal an underlying pattern to the arrangement of nodes and links. In addition, network topologies admit the possibility of gaining insights into the function, purpose and possible future evolution of the entities that are represented by these patterns (Rhodes and Keefe, 2007). For example, in the area of WOM marketing, Van der Lans et al. (2010) used one type of the network topologies – tree topology - to develop models for predicting the WOM volume. In this thesis, complex network topology has been applied to develop models for predicting the WOM volume.

Thus, this thesis will aim to look at the Cause, Development and Outcome of

Word-of-Mouth Marketing: with Particular Reference to WOM Volume, Valence and the Modeling of Viral Marketing. According to previous research on WOM volume (e.g. Krackhardt, 1992; Granovetter, 1973; Kwak et al., 2010; Bakshy et al., 2011; Pandit et al. 2012), the cause, development and outcome of WOM volume in social networks are significantly influenced by network topologies. The modeling of WOM volume in viral marketing will be looking at WOM volume in a variety of social networks including Twitter and Weibo. Specifically, this will attempt to establish dynamic models of WOM volume in viral marketing where there has been little research into the dynamic modeling of WOM volume and the data used in this study would be crawled from the above-mentioned social websites, which will provide a further contribution to the field.

#### 1.1.1 WOM VOLUME

WOM volume, or the number of WOM comments or ratings (Basuroy et al. 2003; Chevalier and Mayzlin 2006; Liu 2006), remains largely under-researched, perhaps because consumers' WOM traditionally reached only a few direct contacts, such as family members and friends, which allowed for little variation in WOM volume. According to Blodgett, Granbois, and Walters (1993), dissatisfied consumers would tell an average of nine others

about their negative experiences, and few publicly available forums enabled consumers to express their opinions. In contrast, the increasing popularity of blogs, discussion boards, online rate-and-review Web sites, and other social media now enable thousands of consumers to post frequent reviews of products and services, which many more potential consumers read before making purchase decisions (Senecal and Nantel 2004). Volume thus has become an important factor in determining the transfer of WOM information (Khare, Labrecque, and Asare, 2011).

In the early research, Krackhardt (1992) and Granovetter (1973) reveal the impact of the strength of strong and weak ties to social works, respectively. Later, some topological properties and network metrics like the number of followers, PageRank value and the number of retweets were used to rank and find the most influential users (Kwak et al. 2010). Based on these, Bakshy et al. (2011) propose diffusion tree to quantify the user influences. Note that the rankings by different influence measures are often inconsistent, and PageRank usually fails to produce high quality target sets dispersing across the whole network (Pandit et al. 2012).

### 1.1.2 WOM VALENCE

The most frequently researched topic in consumers' online reviews is review valence. Online reviews are classified as positive or negative reviews in terms of their directionality (Lee et al., 2009). Although this topic has been studied extensively, the results have failed to produce a consistent conclusion. Most previous research showed that negative information generally has a stronger influence than either neutral or positive information (Herr et al., 1991; Lee et al., 2009; Xue & Zhou, 2010; Yang & Mai, 2010). This tendency has been referred to as negativity bias or the negativity effect. According to this theory, when people form impressions of an object, they are more affected by negative characteristics than positive ones. This negativity effect occurs since negative information is scarcer than positive information (Chiou & Cheng, 2003). Accordingly, individuals pay more attention to negative than positive information, and negative cues are given more weight (Fiske, 1980). Herr et al. (1991) showed that a negative WOM has a stronger impact than a positive WOM. This result is explained by prospect theory, which implies that losses loom larger than gains (Lee, Park, & Han, 2008).

In contrast to these findings, positivity effects have also been found in previous studies (Clemons, Gao, & Hitt, 2006; Gershoff, Mukherjee, &

Mukhopadhyay, 2003; Lee et al., 2009; Skowronski & Carlston, 1989), although they are less frequently studied than negativity effects. Gershoff et al. (2003) showed that positive reviews have a stronger impact than negative ones. Doh and Hwang (2009) showed that positive reviews have a positive significant effect on attitudes and purchase intention. A positivity effect occurs where positive information is considered more diagnostic than negative information. Accordingly, research attesting negativity effects ignore the possibility that opposite effects could occur. In other words, previous research of negativity effects did not expect positivity effects to occur when people rely more on positive information (Skowronski & Carlston, 1989). According to a cue-diagnosticity model, negativity effect does not always occur (Skowronski & Carlston, 1989). Rather, positivity effect is more likely to occur when positive cues are more diagnostic than negative cues. This suggests that when people rely more on positive cues than negative ones, the positivity effect is more likely to occur. Different from negativity or positivity effects, Cheung, Luo, Sia, and Chen (2009) demonstrated that message valence has no impact on message credibility.



### 1.1.3 BACKGROUND – THE SIGNIFICANCE OF VIRAL MARKETING AND ITS DEFINITION

In recent years, conventional means of communication have become increasingly ineffective (Nail, 2005), and have begun to give way to more innovative communication tools due, to a great extent, to the enormous strides in information technologies (IT). With the growth of the Internet, electronic peer-to-peer communication has become a major phenomenon (DeBruyn & Lilien, 2009). Individuals can share opinions and information with others (Hennig- Thureau, Gwinner, Walsh, & Gremler, 2004) more easily and than ever before, virtually free of charge. The Internet is a large-scale means of personalization enabling vast numbers of people to be reached in a one-to-many process, similar to conventional mass media, but with the added advantage of message personalization, for instance through email messages, which resemble interpersonal communication in that they can be tailored to the individual (Phelps, Lewis, Mobilio, Perry, & Raman, 2004). This has led to clients having more power than ever before.

Communication is no longer restricted to the conventional one-way firm to consumer approach, or to more recent two-way or bidirectional communication. Communication now flows in a variety of ways, exploring the

links or relations that individuals have with others through IT. Furthermore, at a time when consumers display ever-diminishing trust in firms and their advertising messages, word-of-mouth (WOM) communications are proving increasingly popular, particularly since the source (which communicates or convey a message) is known by the message recipient, thus influencing consumer beliefs and attitudes (Brown, Broderick, & Lee, 2007; Cheung, Anitsal, & Anitsal, 2007). Yet, the evolution of the Internet, email and the second generation of the web – or web 2.0, the web built by everyone for everyone (such that many to refer to web 2.0 as the social or democratic web) , as well as social media in general (Facebook, Twitter, Blog, etc.) have led to the WOM phenomenon taking on gigantic proportions. Whilst it has traditionally been held that, on average, satisfied consumers pass on their satisfaction to three other people and dissatisfied consumers to eleven, the emergence of IT has meant that the scope and reach of such messages can multiply beyond the mere exponential. For instance, a person in Facebook has an average of around 150 contacts, each of whom in turn has a similar number of contacts in their network. Each message posted on their wall is automatically distributed and sent out to all their contacts and may be commented on, shared or forwarded by these subjects to the same number in their own network. One important point to note is that whilst conventional WOM is virtually restricted to those with whom there is some kind of previous contact or acquaintance (we share our opinions personally with relatives,

friends, work- mates, etc.), when a user posts an opinion on the Internet, the message reaches both those who are known as well as those who are not (in forums, blogs, and even some Twitter followers). Yet, not only is the scope important but also the value which individuals attach to these communications (according to a study published recently in Spain, the results of which do not differ from those obtained in other countries with similar Internet penetration rates – around 50% of the population –, 69% of users normally use the network to check out other people's opinions concerning various products/services, and 43.2% trust the information they see).

Many see viral marketing as a form of WOM advertising in which certain consumers tell others about a product or service (Vilpponen, Winter, & Sundqvist, 2006). Viral advertising relies on provocative content to motivate unpaid peer-to-peer communication of persuasive messages from identified sponsors (Porter & Golan, 2006). In other words, firms must persuade consumers, with the support of IT and through their network of contacts, to become the vehicles through which the advertising campaign is conducted, through clicks, some authors even dubbing it Word-of-Mouse (Xia & Bechwati, 2008). Thus, rather than advertising, what we are in fact witnessing is a kind of publicity.

As expected, academic research has begun to reflect this development, numerous works appearing in recent years addressing this phenomenon. Yet, the current study on the modeling of WOM in viral marketing explicitly study the development of viral marketing as a branching process and the branching process has been focusing on email communication (e.g. van der Lans et al, 2010; Iribarren and Moro, 2011; Jankowski, Michalski, and Kazienko, 2012). Thus this thesis aim to fill in the gap through a new modeling approach incorporates several types of network topologies and use data set from social websites other than email communication.

Steve Jurvetson and Tim Draper (Knight, 1999) first coined the term viral marketing in 1997. The term describes any strategy that encourages individuals to pass on a marketing message to others, creating the potential for exponential growth in the message's exposure and influence. Like viruses, such strategies take advantage of rapid multiplication to explode the message to thousands, indeed millions (Kirby & Marsden, 2006). At the present time, however, a lack of consensus exists concerning any clear definition of what viral marketing is. Whereas for some, viral marketing refers to word-of-mouth (WOM) communication whereby certain people talk to others about a particular product or service (Phelps et al., 2004; Rosen, 2000), for others viral marketing differs from WOM communication in that those who create the

virus have a vested interest in engaging, recruiting or reaching specific individuals in the net. Put differently, the value of the virus for the person who originally spreads it is directly related to the number of other users the virus attracts (Modzelewski, 2000). Therefore viral marketing is marketing applied to WOM (Gruen, Osmonbekov, & Czaplewski, 2006), in other words, the use of WOM as a tool to disseminate the marketing campaign (hence the term buzz marketing which is also used to describe it). It is thus necessary to merge word-of-mouth with network effect theories. Vilpponen et al. (2006) define viral marketing as word-of-mouth communication in situations where positive network effects prevail and where the role of the influencer is active due to positive network effects. According to van der Lans et al (2010), in a viral marketing campaign, an organization develops an online marketing message and stimulates customers to forward this message to members of their social network.

In this thesis, the definition of “viral marketing” follows the definition of van der Lans et al., (2010) as it is up-to date and has been used in other viral marketing research since (e.g. Hinz et al., 2011). Thus the term “viral marketing” refers to the phenomenon by which consumers mutually share and spread marketing-relevant information, initially sent out deliberately by

marketers to stimulate and capitalize on word-of-mouth (WOM) behaviors  
(Van der Lans et al. 2010).

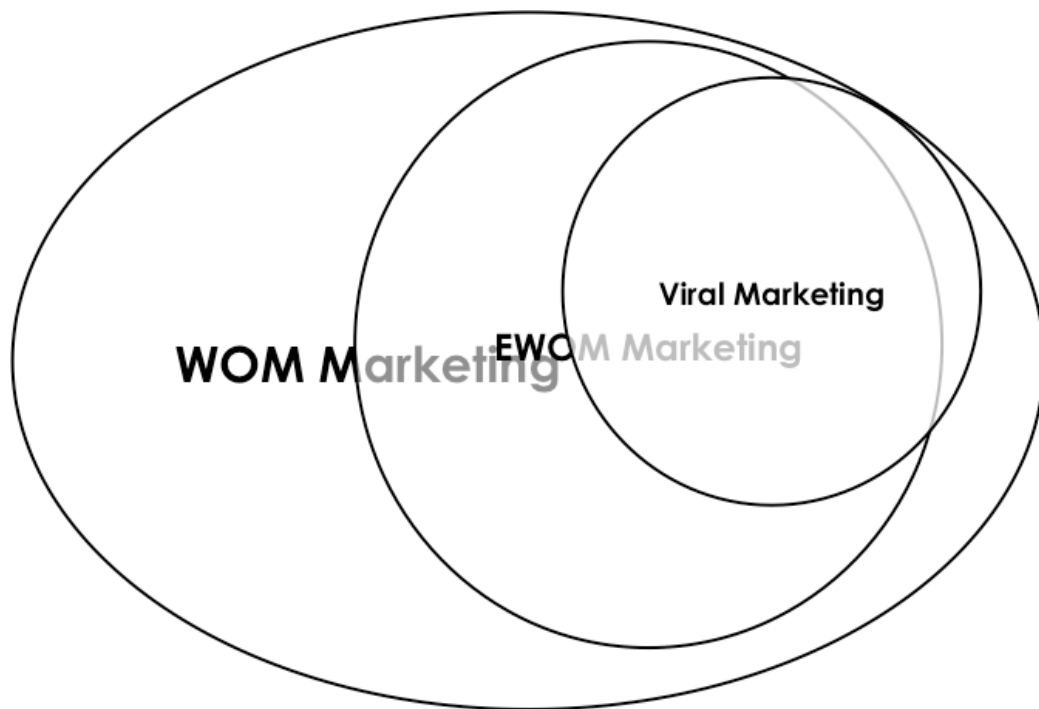


Figure 1 WOM and Viral Marketing

## 1.2 RATIONALE FOR THIS STUDY

In August 2012, Katy Perry tweeted a viral video, *Gangnam style*, on twitter. This tweet generated over 10.9 thousand retweets contributing to over 2.6 million views of the music video on YouTube. On the other hand, in December 2012 in China where people have no access to Twitter but use Microblog (as known as Weibo, the Chinese form of Twitter), a Chinese phone company blogged about its *xiaomi* phone on Weibo. This microblog has generated over 2.6 million reblogs in China. These two examples illustrate a new modern method of marketing communication in which an individual or a company spread information to followers on online social network sites generating high WOM volume and positive WOM valence as well as reaching large numbers of audience in a short period of time. In the industry, big companies such as McDonalds', Coca-Cola and Ford have recently continuously used various online WOM campaigns (also known as viral campaigns) on social websites trying to generate high WOM volume and positive WOM valence. Nevertheless, not all viral marketing campaigns have been successful. Because of the competitive clutter, they need to become increasingly sophisticated in order to be effective and successful (Van der Lans et al., 2010). Moreover, it is critical that marketers are able to make predictions upon the returns on their expenditures, thus important to predict how much WOM volume and valence they will generate from WOM campaigns. As it is stated by one marketing agency: "The move to bring a

measure of predictability to the still-unpredictable world of viral marketing is being driven by clients trying to balance the risks inherent in a new marketing medium with the need to prove return on investment” (Morrissey 2007).

Despite their importance, the only mathematically forecasting tool currently existing is the tree topology model for WOM volume developed by Van der Lans et al. (2010) and their model is for e-mail based online WOM marketing, not WOM in the context of social networking sites. Furthermore, although WOM volume and WOM valence are both critical for WOM marketing as discussed in section 1.1.1 and 1.1.2, there has been no forecasting tools for WOM valence yet. This research will develop a model for predicting WOM volume in social networking sites and also another model for predicting WOM valence in social websites.

Below is a table of the methodologies adopted in previous research on WOM, among which were mostly SEM approach. This research thus contribute methodologically to the WOM literature.



THE CAUSE, DEVELOPMENT AND OUTCOME OF WORD-OF-MOUTH MARKETING: WITH PARTICULAR  
REFERENCE TO WOM VOLUME, VALENCE AND THE MODELING OF VIRAL MARKETING

| <b>Studies of WOM Volume/Valence or Viral Marketing</b>  | <b>WOM Volume</b>   | <b>WOM Valence</b>  | <b>Viral Marketing</b>   | <b>Modeling Dynamic WOM Volume of Viral Marketing</b> | <b>Modeling Dynamic WOM Valence of Viral Marketing</b> |
|--|---|---|--|---|--|
| <b>The Effects of Word-of-Mouth Volume</b><br><br>(e.g. Duan, Gu & Whinston, 2008; Khare, Labrecque & Asare, 2011; Roschk & Grobe, 2013) | Duan, Gu & Whinston, (2008),<br>Roschk & Grobe (2013): Structural equation modeling (SEM) using data from three publicly available websites about movies/ from five publicly available websites about movies<br><br>Khare, Labrecque & Asare (2011): Analysis of variance (ANOVA) using data from two experimental studies (Questionnaires) | Duan, Gu & Whinston (2008): Structural equation modeling (SEM) using data from three publicly available websites about movies | <b>Not analyzed</b>  | <b>None</b>   | <b>None</b>  |
| <b>The Role of Network Topology on Viral Marketing Volume</b><br>(e.g. Bampo et al., 2008; Lee, et al., 2013)                            | Bampo et al. (2008): Simulation experiments using empirical data from a viral marketing campaign conducted by General Motors Holden in Australia and simulated data from three general types of network structures (i.e. Random Networks, Scale-Free Networks and Small World Networks)<br><br>Lee, et al., (2013): Structural equation     | <b>Not analyzed</b>   | Bampo et al. (2008): Inferred<br><br>Lee, et al., (2013): Structural equation modeling (SEM) using data from several online communities in Korea about specific cellular | <b>None</b>   | <b>None</b>  |

THE CAUSE, DEVELOPMENT AND OUTCOME OF WORD-OF-MOUTH MARKETING: WITH PARTICULAR REFERENCE TO WOM VOLUME, VALENCE AND THE MODELING OF VIRAL MARKETING

|  |   |  |                                |             |             |
|--|---|--|--------------------------------|-------------|-------------|
|  | modeling (SEM) using data from several online communities in Korea about specific cellular phone models   |  | phone models                   |             |             |
| <b>The Modeling of WOM Volume</b><br>(e.g. van der Lans et al., 2010; Iribarren and Moro; 2011; Jankowski et al. 2012) | van der Lans et al., (2010), Iribarren & Moro (2011) , Jankowski et al. (2012):<br><br>Mathematical models based on the assumption of branching process where customers participated viral marketing campaign by responding to a seeding e-mail from the organization | <b>Not analyzed</b>  | Inferred                       | <b>Yes</b>  | <b>None</b> |
| <b>The Effects of Word-of-Mouth Valence</b><br>(e.g. Huang, et al., 2011; Yang, et al., 2012; Lee & Koo, 2012)         | Yang, et al. (2012): Structural equation modeling (SEM) using data from the motion picture industry   | Huang, et al. (2011), Yang, et al. (2012): Structural equation modeling (SEM) using data from the motion picture industry/from a survey based on real posts in online discussion forums<br><br>Lee & Koo (2012): ANOVA using data from experiments where students in courses such as advertising and management logged into the experimental | Huang, et al. (2011): Inferred | <b>None</b> | <b>None</b> |

THE CAUSE, DEVELOPMENT AND OUTCOME OF WORD-OF-MOUTH MARKETING: WITH PARTICULAR  
REFERENCE TO WOM VOLUME, VALENCE AND THE MODELING OF VIRAL MARKETING

|  |  |   |   |             |             |
|--|--|---|---|-------------|-------------|
|  |  | Website and answered survey questions (Surveys)   |   |             |             |
| <b>The Antecedents of Word-of-Mouth Valence</b><br>(e.g. Edwards & Edwards, 2013; Rui, Liu & Whinston, 2013) | <b>Not analyzed</b>  | Edwards & Edwards (2013): One-way K-group multivariate analysis of variance (MANOVA) and ANOVA using data from surveys.<br><br>Rui, Liu & Whinston, 2013 Structural equation modeling (SEM) using data of which movie sales data were collected from BoxOfficeMojo.com and tweet information was collected from Twitter |   | <b>None</b> | <b>None</b> |
| <b>This Research</b>   | Mathematical models based on network topologies using data crawled from social websites and computer simulation experiments. | Artificial Neural Network (ANN) models where input variables were statistically examined with meta-analysis, using data from social websites and computer simulation experiments  | Analyzed using the WOM volume and valence model in viral marketing. | <b>Yes</b>  | <b>Yes</b>  |

Table 1 Previous Literature on WOM

### 1.3 DISTINGUISHING WOM AND EWOM

Although both WOM and EWOM share similar characteristics such as both having the components of a source, a message and a receiver (Fadel, Alsaqa & Al-Fedaghi, 2009), dimensional distinctions between WOM and EWOM suggest that one same mechanism for WOM cannot be directly applied for EWOM. Dimensional distinctions between WOM and EWOM have been conceptualized by Tham, Croy and Mair (2013), and it is shown in table 1. In fact, assessing the spread of EWOM is more complex than is the case of traditional WOM due to the context of the Internet (Tham, Croy and Mair, 2013). The model development in this thesis thus focused on the modeling of EWOM, not traditional WOM..

| Dimensional Difference        | WOM                                     | EWOM   |
|-------------------------------|---|--|
| Source-receiver relationships | Known and established                   | Potentially unknown source and receiver                              |
| Channel variety               | Typically through face to face or phone | Mediated over technology and across different online community sizes |

|                                       |   |   |
|---------------------------------------|---|---|
| Information solicitation              | Depend on known sources and existing source profile | Wide scope for unknown sources and range of source profiles |
| Message retention                     | Based on ability to recall                          | Representation stored online                                |
| Motivation for disclosing information | Assistance in making informed decisions             | In addition to decision making, opportunities to socialize  |

Table 2 Dimensional Differences between WOM and EWOM (Tham, Croy and Mair, 2013)

#### 1.4 AIMS AND SCOPE OF THE STUDY

The extant literature review for this research consists of seven sections which are Section 1 Overview of WOM and Viral Marketing, Section 2 The Cause of Word-Of-Mouth Marketing: with Particular Reference to WOM Volume, Valence and the Modeling of Viral Marketing, Section 3 The Development of Word-Of-Mouth Marketing: with Particular Reference to WOM Volume, Valence and the Modeling of Viral Marketing, Section 4 The Outcome of Word-Of-Mouth Marketing: with Particular Reference to WOM Volume, Valence and the Modeling of Viral Marketing,

Therefore the aim of this study is to provide a new insight into the Modeling of WOM Volume and Valence in viral marketing that “traditional” research on WOM Volume and Valence has neglected. The theory of network topologies in social network marketing will be used as a conceptual base to model the WOM volume in viral marketing; The theory of artificial neural network in consumer online evaluation process will be used as a conceptual base to model WOM valence in viral marketing. This will provide dynamic models that describe the developments of WOM volume in viral marketing. The models can be used for forecasting the WOM volume outcome in the future. Moreover, artificial neural network WOM valence models simulate the development of WOM valence and can be used for forecasting the WOM valence outcome. These models will contribute to the current literature academically and assist the decision-making of marketers to achieve successful viral marketing campaigns in practice.

Specifically, the research objectives are:

- 1) To examine the extant literature of WOM and viral marketing and identify the conceptual developments regarding the cause, development and outcome of word-of-mouth marketing: with particular reference to WOM volume, valence as well as identify previous modeling approaches from the aforementioned literature. Core research questions with regard to this

objective are:

1) To examine the extant literature of WOM and viral marketing regarding the cause, development and outcome of word-of-mouth marketing: with particular reference to WOM volume, valence and viral marketing

- To identify the most important WOM attributes for the modelling of viral marketing.
- To identify the most important factors that affect WOM volume
- To examine the modeling approaches for WOM volume in viral marketing
- To select the modeling approach for WOM volume in viral marketing
- To identify the most important factors that affect WOM valence
- To examine the modeling approaches for WOM valence in viral marketing
- To select the modeling approach for WOM valence in viral marketing

2) To carry out the necessary collection of data using web crawling, and computer simulations

3) To develop mathematical models that describe the dynamics of WOM volume and valence in viral marketing.

Previous WOM studies mixed the modeling of WOM volume and valence together. However, this thesis propose that the modeling of WOM volume growth can be described by WOM diffusion model as a diffusion model describes the accumulation of WOM spread; the modeling of WOM valence can use dynamic ANN models as WOM valence depends on the emotion of a WOM participant and ANN models could simulate and predict the emotion dynamics from a general customer's perspective.

Moreover, research questions of this study are listed as followings:

- Why are WOM and viral marketing research important?
- Which attributes of WOM marketing are the most important and therefore should be used in the modeling of WOM?
- What is the cause of WOM?
- How does WOM develop?
- What is the outcome of WOM?
- How to model WOM volume and what are the models for the modeling of WOM volume in viral WOM marketing?
- What affects WOM valence and therefore needs to be considered for the modeling of viral marketing?
- How to model WOM valence in viral marketing?
- What is the WOM valence model in viral marketing?
- How to collect data for the modeling of viral WOM?



## 1.5 OVERVIEW OF THE THESIS

The thesis is divided into five chapters:

Chapter One defines the research area and statement of the problem. It provides an overview of the aim and objectives of the study and it outlines the structure of the thesis. It also provides a general background and defines WOM and viral marketing and their significance.

Chapters Two examine the topic of WOM and viral marketing and review the literature relevant to the main research objectives of the study-the cause, development and outcome of word-of-mouth marketing: with particular reference to WOM volume, valence and the modeling of viral marketing

Chapter Three of the thesis discusses the research methodology. The first section concerns the philosophical positioning of this study and the underpinning rationale of selecting the positivist philosophy. The second section of this chapter involves the research methodology and research design adopted, consisting of a plan and structure as to how WOM volume and WOM valence models could be developed. It deals with sample selection and data collection.

Chapter Four constitutes the analysis of the research and discussion of the findings. The WOM volume and WOM valence models were analysed.

Chapter five concludes and discusses the contributions to knowledge that this thesis will hope to make.

### *Conclusion*

This chapter has defined the research area and theoretical research problems. It has outlined the research objectives and research questions of this study and provided an overview of intended content. Finally, it has provided a general background on WOM and viral marketing and the importance of this research.

## **CHAPTER TWO**

### **LITERATURE REVIEW**

The literature review for this thesis will be discussed in this chapter: It will examine WOM and viral marketing and then narrow down by focusing in on the modeling of WOM volume and WOM valence. This will review the literature, which is relevant to the main research objectives of this study

#### **2.1 WOM AND VIRAL MARKETING: AN INTRODUCTORY OVERVIEW**

##### **2.1.1 INTRODUCING WOM AND VIRAL MARKETING**

As stated in Chapter 1, The term "word of mouth" (WOM) refers to the flow of communications among consumers about products and services (Westbrook 1987). The term "viral marketing" refers to the phenomenon by which consumers mutually share and spread marketing-relevant information, initially sent out deliberately by marketers to stimulate and capitalize on word-of-mouth (WOM) behaviors (Van der Lans et al. 2010).

Word-of-mouth communications have received extensive attention from both academics and practitioners for decades. Since the early 1950s, researchers have demonstrated that personal conversations and informal exchange of information among acquaintances not only influence consumers' choices and purchase decisions (Arndt, 1967; Whyte, 1954), but also shape consumer expectations (Anderson & Salisbury, 2003; Zeithaml & Bitner, 1996), pre-usage attitudes (Herr, Kardes, & Kim, 1991), and even post-usage perceptions of a product or service (Bone, 1995; Burzynski & Bayer, 1977). Some research has reported WOM influence as greater than print ads, personal selling, and radio advertising (Engel, Kegerreis, & Blackwell, 1969; Feldman & Spencer, 1965; Katz & Lazarsfeld, 1955). Compared to traditional marketing communication tools, WOM is perceived to be more trustworthy and relevant, is more likely to generate empathy, and can significantly reduce consumer resistance (Bickart and Schindler, 2001), although Van den Bulte and Lilien (2001) show that some of those effects may have been overstated.

WOM has been described as “a dominant market force in the marketplace” (Mangold, Miller, and Brockway, 1999), and some researchers have suggested that WOM plays a significant role-often more than any other source-in influencing consumers’ perceptions of a firm (Allsop, Bassett, and Hoskins, 2007). Silverman (2001) claimed that WOM is the most powerful way of

communication because it is driven by customers themselves. People choose with whom to talk and what to ask. When people actively search for WOM, they are more involved in that communication. According to the elaboration likelihood model (Petty and Cacioppo, 1983, 1984), people use a central route to process the message; in other words, they pay more attention to or expend more cognitive effort on the message.

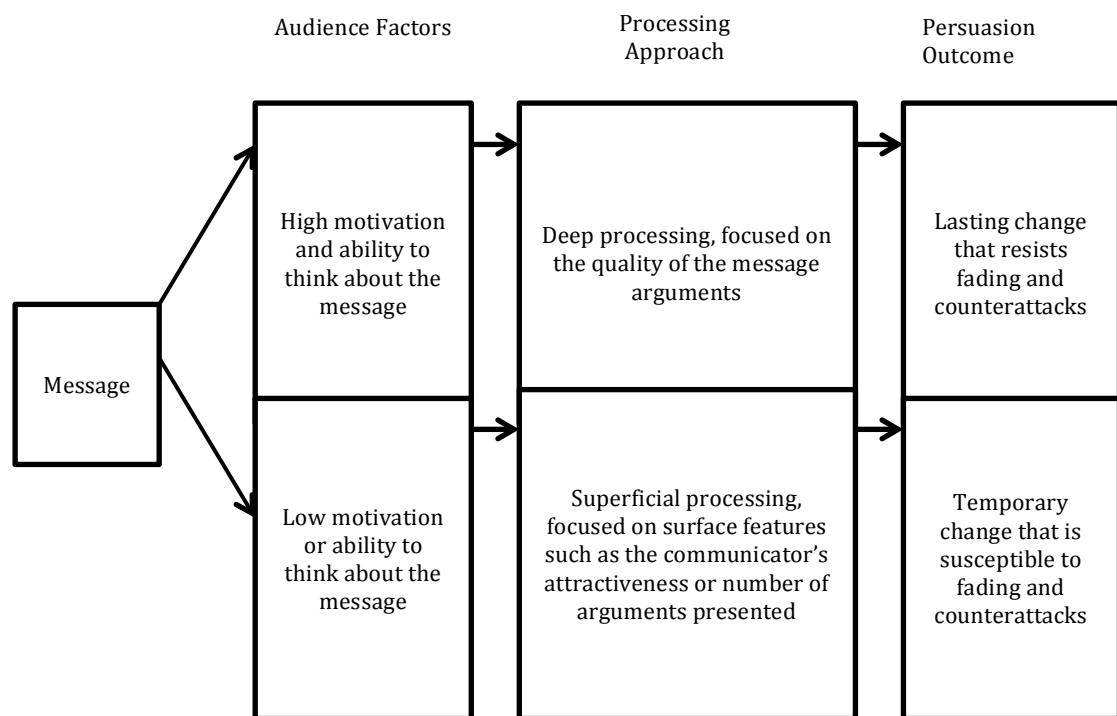


Figure 2 Elaboration Likelihood Model (ELM) (Kenrick, Neuberg, and Cialdini, 2002)

The elaboration likelihood model (ELM) probably is the most influential theoretical framework in the persuasion literature because it integrates research findings related to source, message, recipient, and contextual effects (Petty and

Cacioppo, 1986). According to the ELM, people's motivation and ability to assess the central merits of a message can trigger qualitatively different processing styles. Petty et al. (1981) found that people who have a higher level of involvement are more likely to change their attitude when the argument is strong.

The modern consumer's ability to absorb information, as well as to share opinions and experiences about products, brands, purchases, organisations and websites has substantially increased (Smith, 2011). Banking, e-mail, social networking, making travel reservations, and watching videos are just some of the common activities that users engage in online, with roughly one-third of all users reporting these activities (Zickuhr, 2010). Moreover, some 56 percent of internet users have logged in with a wireless internet connection at home, work, or someplace else (Horrigan, 2009). In addition, The Internet dramatically facilitates consumer interconnections. As a consequence of Internet, social networking and interactive technologies, consumers have become increasingly engaged in word-of-mouth (WOM) and viral marketing activity (Chadwick, 2003). With the popularization of the Internet, WOM began to offer the promise of becoming an emerging advertising discipline (Plummer, 2007). Further, consumers routinely forward promotional material and information about products and companies to friends and colleagues. Faced with a rapid decline of consumer trust in traditional advertising, companies are looking for

different ways to promote products; consequently, word-of-mouth marketing has gained ground (Verlegh and Moldovan, 2008). Indeed, Urban (2004) suggests that viral WOM might replace traditional mass media as the central mode of influence on consumer attitudes and brand choices, and as Dellarocas (2003) noted, WOM, in particular, is becoming a popular cornerstone of information for consumer decision-making and choices.

A corollary of increasing competition regarding e-commerce business and websites clamouring for attention and retention is that e-retailers, at best, seem to have a tenuous hold on their customers' loyalty. There is a need for online marketers to retain and continuously attract new customers to their websites to maintain a stream of profitability (Ray & Chiagouris, 2009). Many scholars see a company's ability to motivate positive WOM behaviours from their customers and visitors as a strategic opportunity to achieve several aspects of customer loyalty. Numerous marketing studies suggest that potential customers are likely to adopt a product or a service when positive WOM information is disseminated to them from their peers (Roy, 2013).

One of the fastest-growing arenas of the World Wide Web is the space of so-called social networking sites. A social networking site is typically initiated by a small group of founders who send out invitations to join the site to the

members of their own personal networks. In turn, new members send invitations to their networks, and so on. Thus, invitations (i.e., WOM referrals) have been the foremost driving force for sites to acquire new members.

Typical social networking sites allow a user to build and maintain a network of friends for social or professional interaction. The core of a social networking site consists of personalized user profiles. Individual profiles are usually a combination of users' images (or avatars); lists of interests and music, book, and movie preferences; and links to affiliated profiles ("friends"). Different sites impose different levels of privacy in terms of what information is revealed through profile pages to nonaffiliated visitors and how far "strangers" versus "friends" can traverse through the network of a profile's friends. Profile holders acquire new friends by browsing and searching through the site and sending requests to be added as a friend. Other forms of relationship formation also exist.

In the past few years, social networking sites have become extremely popular on the Internet. According to comScore Media Metrix (2006), every second Internet user in the United States has visited at least one of the top 15 social networking sites. Approximately 50 social networking Web sites each have



more than one million registered users, and several dozen smaller, though significant, sites also exist. Compete.com (2013), a Web traffic analysis company, reported that the largest online social networking site (as of November 2013) was Facebook, with 1.23 billion monthly active users.

The term “viral marketing” describes the phenomenon by which consumers mutually share and spread marketing-relevant information, initially sent out deliberately by marketers to stimulate and capitalize on word-of-mouth (WOM) behaviors (Van der Lans et al. 2010). The most common version of intentional viral marketing occurs when consumers willingly become promoters of a product or service and spread the word to their friends; they are driven to do so either through an explicit incentive (e.g., financial incentives, need to create network externalities) or simply out of a desire to share the product benefits with friends (e.g., fun, intriguing, valuable for others). As examples, PayPal, by providing financial incentive to have members recommend members, acquired more than three million users in its first nine months of operation. Moreover, Compared to traditional WOM, online WOM communication spreads at an unprecedented speed for a much lower cost. These characteristics parallel the traits of infectious diseases, such that the name and many conceptual ideas underlying viral marketing build on findings from epidemiology (Watts and Peretti 2007).

### 2.1.2 THE EFFECTIVENESS OF WOM AND VIRAL MARKETING

Historically, marketers have recognized the power of WOM communication to inform, motivate, and influence opinions, purchases, and recommendations for products and services. Considering that WOM has been shown to be more effective than traditional marketing tools like personal selling and advertising (Bickart and Schindler, 2001; Goldsmith and Horowitz, 2006)

The earliest study on the effectiveness of WOM is survey based (Katz and Lazarsfeld, 1955) and was followed by more than 70 marketing studies, most of them also inferring WOM from self-reports in surveys (Godes and Mayzlin 2004; Money, Gilly, and Graham, 1998). Researchers have examined the conditions under which consumers are likely to rely on others' opinions to make a purchase decision, the motivations for different people to spread the word about a product, and the variation in strength of people's influence on their peers in WOM communications. Moreover, customers who self-report being acquired through WOM add more long-term value to the firm than customers acquired through traditional marketing channels (Villanueva, Yoo, and Hanssens 2008).

For many firms, marketing spending on acquiring customers represents an important expense, and it is widely known that the acquisition process has an important effect on future retention probability (Thomas 2001). Researchers have also investigated the effectiveness of different marketing communication channels and have provided models to allocate the acquisition budget for future profitability (e.g., Reinartz, Thomas, and Kumar 2005). Conversely, customers can also be acquired spontaneously from WOM communications, newspaper articles, user reviews, or Internet search results. An increasing number of firms encourage WOM with or without monetary incentives. For example, BMG Music Service not only spends on online ad banners and direct mail but also gives referral incentives (in the form of free CDs) to existing customers to increase the buzz level. Netflix, an online DVD rental firm, encourages referrals without any monetary incentive. Although these types of customer acquisition are less controlled by the firm, they may be more likely to succeed, for various reasons. First, these communications have greater credibility than conventional marketing activities that are designed and implemented by the firm. For example, it has been suggested that WOM communications are more persuasive than conventional advertising (Brown and Reingen, 1987; Herr, Kardes, and Kim, 1991). Second, contingent persuasion knowledge theory (Friestad and Wright 1994, 1995) suggests that customers realize that the main goal of marketing communications is to influence their beliefs and/or attitudes about the firm and therefore cope with these attempts. Third, because these

communications can spread with less support from the firm's marketing resources, the firm can enjoy larger financial gains from customer acquisition.

Researchers show that WOM dynamically influences demand or customer acquisition (Liu 2006; Moe and Trusov 2011; Trusov, Bucklin, and Pauwels 2009). Similar rationales in support of dynamic ad effectiveness would also apply to dynamic WOM effectiveness. As the volume and valence of WOM vary within a distribution stage or across stages, its content, usability, and strength at signifying product appeal may change, thus altering its impact on demand.

Table 3 below made a comparison of previous studies on the effectiveness of WOM.

| Comparison of Empirical Studies on the Effectiveness of WOM |                          |  |   |  |
|---|--------------------------|--|---|--|
|   | WOM Inference            | Effect of WOM on Customer Acquisition            | Comparison with Traditional Marketing                 | Indirect Effects of WOM and/or Traditional Marketing |
| Initial (Katz and Lazarsfeld 1955) and most studies         | Self-report from surveys | Inferred from self-reports on relative influence | WOM two times more effective than radio advertisement | Not analyzed   |

|  |  |   |  |   |
|--|--|---|--|---|
|  |  |   | nts, four<br>times more<br>than<br>personal<br>selling,<br>seven times<br>more than<br>print<br>advertiseme<br>nts                                   |   |
| Customer<br>lifetime<br>value<br>(Villanueva,<br>Yoo, and<br>Hanssens<br>2008)                           | Inferred<br>from new<br>customer's<br>self-report                        | Not analyzed  | Customers<br>acquired<br>through<br>WOM add<br>two times<br>the lifetime<br>value of<br>customers<br>acquired<br>through<br>traditional<br>marketing | Customers<br>acquired<br>through<br>WOM spread<br>more WOM<br>and bring in<br>twice as<br>many new<br>customers |
| Social<br>contagion<br>(Coleman,<br>Katz, and<br>Menzel<br>1966; Van<br>den Bulte<br>and Lilien<br>2001) | Inferred<br>from<br>adoption   | Difficult<br>to<br>attribute<br>observed<br>contagion<br>to WOM<br>versus<br>traditional<br>marketing | Contagion<br>effects<br>disappear<br>when<br>traditional<br>marketing<br>effects are<br>included in<br>the model                                     | Not analyzed  |
| Determinan<br>ts of WOM<br>transmissio<br>ns (Stephen<br>and<br>Lehmann                                  | Directly:<br>person's<br>decision to<br>transmit<br>WOM in<br>experiment | Expected<br>responsiven<br>ess of<br>WOM<br>recipient<br>drives                                       | None   | Not analyzed  |

|   |   |   |  |  |
|---|---|---|--|--|
| 2008)   | al setting  | transmitter's<br>decision to<br>pass WOM                                  |  |  |
| Valence of<br>online<br>WOM<br>(Chevalier<br>and Mayzlin<br>2006;<br>Liu, 2006)   | Inferred<br>from<br>Website<br>posts and<br>reviews | Higher<br>number of<br>reviews<br>leads to<br>higher<br>relative<br>sales | None   | Not analyzed   |
| Impact of<br>social ties<br>on WOM<br>effect (De<br>Bruyn and<br>Lilien<br>2008)  | Directly:<br>though<br>e-mails<br>sent              | Social tie<br>effects<br>depend on<br>stage of<br>decision<br>making      | None   | Not analyzed   |
| Effects of<br>Word-of-M<br>outh<br>regarding<br>Internet<br>Social<br>Networking<br>Site<br>(Trusov,<br>Bucklin,<br>Pauwels,<br>2009) | Directly:<br>through<br>referrals sent              | Quantify<br>direct and<br>indirect<br>effects of<br>WOM and<br>marketing  | Compare<br>immediate<br>and carryover<br>effects of<br>WOM and<br>traditional<br>marketing | Demonstrate<br>indirect<br>effects and<br>quantify total<br>monetary<br>value of<br>WOM activity |

Table 3 the Comparison of Empirical Studies on the Effectiveness Of WOM

### 2.1.3 THE RIPPLE EFFECT OF WOM

As a powerful communication tool, WOM could have two distinctive functions - persuasion and the ripple effect caused by WOM diffusion (Weening and Midden, 1991; Hogan et al., 2004; De Bruyn and Lilien, 2004) corresponding to the positive WOM valence and high WOM volume. Most studies in the extant literature have treated WOM as persuasive communication and focused only on the persuasive effect (Weening and Midden, 1991). Some studies have also treated WOM as diffusive communication. The diffusion of WOM helps generate a ripple effect for marketing activities, which is also called BUZZ marketing (Phelps et al., 2004; Verlegh and Moldovan, 2008). WOM advertising is a highly valuable tool for advertisers because WOM can serve both as a measure of advertising's effectiveness and as a highly credible source of information about a new brand (Plummer, 2007). The extent to which the effect of advertising is extended (or multiplied) by WOM is called advertising ripple effect caused by WOM (Hogan et al., 2004). The ripple effect has been identified as being able to significantly multiply or extend the effectiveness of advertising (Hogan et al., 2004). For example, initial marketing activities (advertisement, promotion) trigger initial purchase reactions, and that purchase experience subsequently triggers the spread of WOM, as customers share their

experiences with others (Chevalier and Mayzlin, 2006). The ripple effect is of primary importance to marketers and policy-makers since it allows a stimulus intended for one individual to be magnified by its dispersion through a network. From a normative point of view, the ripple effect of WOM may vastly increase the return-on-investment and, hence, becomes a significant interest for firms. Scholars have theoretically and empirically demonstrated that WOM can influence consumer behaviour and, consequently, increase the effectiveness of advertisements (Mayzlin, 2006; Hogan et al., 2004). Given the importance of the ripple effect to marketers, widening the ripple effect of WOM is one area of great interest to marketers. Beyond knowing about the existence of the ripple effect, we also need to understand how to generate a bigger ripple effect for marketing activities, which leads researchers to fill the gap with the modeling of WOM volume. In this research, the author try to model WOM volume which would contribute to widening the ripple effect of WOM (see Figure 1).



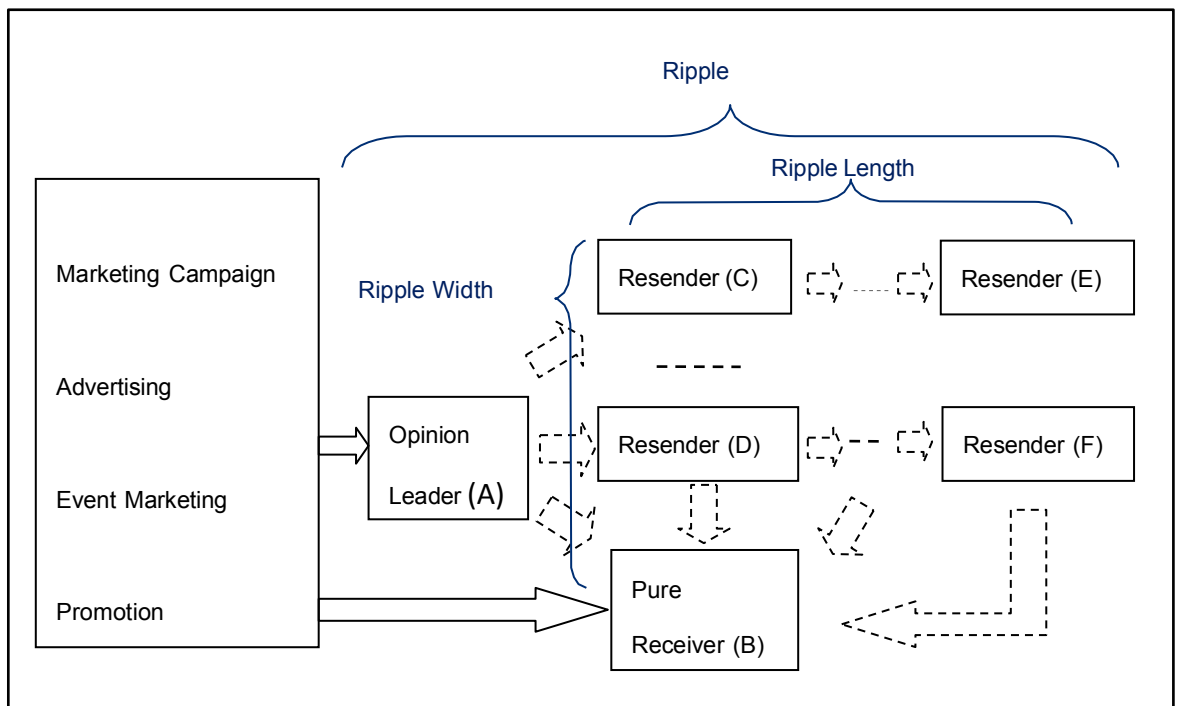


Figure 3 The Ripple Effect of WOM

#### 2.1.4 THE DIFFERENCES BETWEEN ONLINE WOM AND OFFLINE WOM

Online WOM is also called eWOM. For purposes of clarity and consistency, definitions for electronic word-of-mouth (eWOM) is provided. This research adopts the definition of eWOM provided by Hennig-Thurau et al. (2004, p. 39) as:

[. . .] any positive or negative statement made by potential, actual or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet.

Online WOM (EWOM) is similar to personal selling in that it provides explicit information, tailored solutions, interactivity, and empathetic listening, but it has a lower “distance” between the source of communication and the receiver than marketer-induced communications (Hung and Li, 2007, p. 486). Others believe that there is a fundamental difference between online and offline WOM exchanges; specifically, consumers seem to accept the reviews, advice, and opinions of strangers online in a completely different way than has been seen in traditional WOM (Hennig-Thurau and Walsh, 2003; Vilpponen et al., 2006).

For instance, taking online recommendations or advice may be more powerful due to the viral nature and reach of eWOM. eWOM may also carry more weight due to its print format as compared to the purely verbal exchange of traditional WOM and, finally, eWOM may in fact create more influence since the internet allows access to information at the exact moment the user seeks it out. In contrast, eWOM is significantly less personal than traditional WOM, which may in fact lessen its impact. However, research has shown that the “likeness” (homophily) of people online is not particularly important (in stark contrast to typical WOM exchanges); rather, shared group interests and mindsets are of higher value (Balasubramanian and Mahajan, 2001; Bearden and Etzel, 1982; Dwyer, 2007; Edwards, 2006; Hagel and Armstrong, 1997; Kiecker and Cowles, 2001; Mayzlin, 2006; Sussan et al., 2006). Similarly, the idea of the strength of close ties in eWOM is not as important as it is in interpersonal one-on-one communications. Perhaps it is best to consider the Internet itself as the “bridge” between groups, but the actual “influence” is created within the specific shared interest forum, discussion board, blog, or online review. This notion raises the question of how credibility might be assessed, evaluated, and valued by consumers online and is of interest considering that, “Similar to WOM, research has shown that eWOM may have higher credibility, empathy and relevance to customers than marketer-created sources of information on the Web”, (Gruen et al., 2006, p. 449).

Offline WOM is defined as face-to-face communication between participants (Arndt, 1967, 1968). Offline WOM requires resenders and receivers to interact in real time, which is termed as "temporal synchronicity" by Hoffman and Novak (1996). These resenders and receivers must know each other, must have some form of social ties and must exchange information using verbal communication. Furthermore, after receiving information, resenders in offline WOM have to remember the information and then transmit it to others. Thus, the offline flow path is difficult to analyze, and hence the resender's role is rarely considered. In offline WOM, senders and receivers know each other and communicate face to face, receivers' acceptance towards WOM information could be influenced by the senders' individual characteristics, such as strength of ties (Feick and Price, 1987; Frenzen and Nakamoto, 1993). Since people are usually anonymous in an online environment, the senders' individual characteristics are not available, or need to be inferred from the WOM information. Therefore, in an online environment, receivers have to put more weight on WOM information per se when they evaluate one piece of WOM information.

Offline WOM includes personal referrals from friends, colleagues, or acquaintances and accidental referrals from unacquainted people in local regions. Online WOM includes referrals through online message boards, blogs, and online communities. Online search includes paid and organic keyword

search from search engines and connections from sponsored price comparison sites. A comparison of online WOM and offline WOM is shown in Table 4 which illustrates the differences between online and offline WOM.

Although WOM is an alternative for advertising, it is hard to manage as marketers cannot control consumers' oral communication content in an offline environment. The internet, in which most of the information is in written format, makes it possible to track, copy and analyze WOM content (Godes and Mayzlin, 2004). Therefore, marketers could have more control over WOM in an online environment than in an offline environment. As shown by Hoffman and Novak (1996), online WOM communication, like WOM in an offline environment, could be one to one (e.g. e-mail, voice e-mail, etc.) or one to many (e.g. group e-mail). As a new form of interpersonal influence, online WOM could be a many to many communication process (e.g. online discussion forums) in which the sources and receivers may be unknown to each other. This provides a chance for companies to manage the WOM information. Furthermore, the ripple effect in essence is driven by social interaction among people. In online discussion forums, many-to-many communication significantly enlarges the scope of social interaction, consequently making the ripple effect bigger. Theoretically, relative to an offline environment, online discussion forums can provide not only a better environment for social

interaction but also a better opportunity for marketers to manage WOM information. In practice, spending on online social networks (e.g. discussion forums) advertising is already at \$280 million (about 2 per cent of all online advertising spending) and expected to reach about \$2 billion (6 per cent of all online advertising) in 2010 (Hartmann et al., 2008).

Table 4 illustrates the comparison between online WOM and offline WOM.

|                 | Offline WOM                  | Online WOM (EWOM)                                   |  |
|-----------------|------------------------------|---|--|
|                 |                              | One-to-one/many diffusion                           | Many-to-many diffusion                               |
| Characteristics |                              |   |  |
| Communication   | Talk, telephone,             | E-mail, text  | Discussion   |
| Medium          | Meeting<br>(letter)          | Chatting<br>(voice chatting)                        | Blog, social website                                 |
| Form            | Oral (written) communication | Written (oral) communication                        | Written communication                                |
| Synchronicity   | Synchronous communication    | Could be asynchronous/<br>Synchronous communication | Could be asynchronous /<br>Synchronous communication |

| Type of interaction                      | Face-to-face interaction/<br>direct                    | Virtual interaction/<br>indirect   | Virtual interaction/<br>indirect                             |
|--|--|--|--|
| Format                                   | Mostly linear communication                            | Linear or non-linear communication   | Non-linear communication                                     |
| Relationship between sender and receiver | Know each other/real social ties/limited receiver pool | Know each other (anonymous)/real (virtual) social ties/ bigger receiver pool | Generally anonymous virtual social ties/bigger receiver pool |
| Ease of transmission                     | Difficult to transmit                                  | Easy to transmit/<br>forward   | Easy to transmit/<br>forward                                 |
| Consequence                              |  |  |  |
| Ripple effect                            | Low ripple/multiplier effect (isolated WOM)            | Middle ripple/multiplier effect (WOM flow)                                   | High ripple/multiplier effect (WOM flow)                     |
| Focus                                    | Focus on persuasive communication                      | Focus on persuasive communication  | Focus on both persuasive and diffusive communication         |
| Critical role                            | Opinion leaders as critical role                       | Opinion leaders as critical role   | Resenders as critical role                                   |

Table 4 Online WOM and Offline WOM

Note : Based on Hoffman and Novak (1996), Huang et al (2011)

Based on the conceptual development of eWOM (Dellarocas, 2003), previous studies have examined the roles and effects of eWOM in online shopping contexts, such as in sales (Brown et al., 2005; Chevalier & Mayzlin, 2006; Lee et al., 2011; Zhu & Zhang, 2010) and business performance (Duan et al., 2008). In particular, previous research has identified several motivators related to eWOM activities, such as commitment (Brown et al., 2005), customer perceptions of product value (Gruen et al., 2006), and identity (Forman et al., 2008). However, the role and effects of eWOM have been examined only in the context of a single online vendor (Brown et al., 2005; Chen et al., 2011; Chevalier & Mayzlin, 2006; Forman et al., 2008; Gruen et al., 2006; Lee et al., 2011; Mudambi & Schuff, 2010) or a single industry (Duan et al., 2008; Zhu & Zhang, 2010). In contrast, there has been little research on eWOM in the context of WOM volume and valence in social websites (viral marketing).

Table 5 shows the summary of previous research on EWOM

| Research            | Objective   | Context                                  | Findings  |
|---------------------|---|--|---|
| Brown et al. (2005) | To investigate the antecedents of positive eWOM, including consumer identification and commitment | An automobile dealership's customer base | Consumer commitment mediates the relationship between satisfaction and positive WOM |



|                                       |   |   |   |
|---------------------------------------|---|---|---|
|                                       |   |   | intentions<br>and<br>behaviors.   |
| Chen et al.<br>(2011)                 | To examine<br>how WOM<br>and<br>observational<br>learning (OL)<br>interact to<br>influence sales      | Amazon.com                                  | While<br>negative<br>WOM is<br>more<br>influential<br>than positive<br>WOM,<br>positive OL<br>information<br>significantly<br>increases<br>sales, but<br>negative OL<br>information<br>has no effect. |
| Chevalier<br>and<br>Mayzlin<br>(2006) | To examine<br>the effect of<br>consumer<br>reviews on<br>relative sales<br>of books                   | Amazon.com<br>and<br>Barnesandnoble.<br>com | An<br>improvement in a<br>book's<br>reviews<br>leads to an<br>increase in<br>relative<br>sales at that<br>site.   |
| Duan et al.<br>(2008)                 | To explicitly<br>model the<br>positive<br>feedback<br>mechanism<br>between<br>WOM and<br>retail sales | Movie industry                              | Both a<br>movie's box<br>office<br>revenue and<br>WOM<br>valence<br>significantly<br>influence  |

|                      |  |   |  |
|----------------------|--|---|--|
|                      | and identify their dynamic interrelationships  |   | WOM volume. WOM volume in turn leads to higher box office performance.   |
| Forman et al. (2008) | To examine the relationship between reviews and sales  | Amazon.com  | Identity-relevant information about reviewers shapes community member judgments of products and reviews.   |
| Gruen et al. (2006)  | To investigate the effects of a specific form of eWOM communication, customer-to-customer know-how exchange, on customer perceptions of value and customer loyalty | Internet user forum of a popular software product | Customer know-how exchange impacts customer perceptions of product value and likelihood to recommend the product, but does not influence customer repurchase intentions. |

|                                 | intentions   |                            |   |
|---------------------------------|--|----------------------------|---|
| Lee et al.<br>(2011)            | To investigate<br>the impact of<br>eWOM on<br>sales<br>distribution  | Amazon.com                 | The more<br>product<br>attributes that<br>need to be<br>evaluated,<br>the more<br>strongly<br>eWOM will<br>exhibit the<br>long tail<br>phenomenon.  |
| Mudambi and<br>Schuff<br>(2010) | To examine<br>the<br>antecedents of<br>the<br>helpfulness of<br>customer<br>reviews                        | Amazon.com                 | Review<br>depth has a<br>positive<br>effect on the<br>helpfulness<br>of the<br>review, but<br>the product<br>type<br>moderates<br>the effect of<br>review depth<br>on the<br>helpfulness<br>of the<br>review. |
| Zhu and<br>Zhang<br>(2010)      | To examine<br>how product<br>and<br>consumer<br>characteristic<br>s moderate<br>the influence<br>of online | The video<br>game industry | Online<br>reviews are<br>more<br>influential<br>for less<br>popular<br>games and<br>games whose   |

|  |   |  |   |
|--|---|--|---|
|  | consumer<br>reviews on<br>product sales |  | players have<br>greater<br>Internet<br>experienc. |
|--|---|--|---|

Table 5 Summary of Previous Research on EWOM

There is growing recognition of the social mechanism underlying WOM and the importance of making it an integral part of a firm's strategy. For online marketers, at least, customer acquisition through referrals and WOM has become an important goal (Roy, Lassar, & Butaney, 2014). WOM has a much stronger impact on consumer's purchasing decisions than traditional promotional tools such as advertising, personal selling or in-store demonstrations. Well entrenched in the literature are the downstream effects of the antecedents of WOM, for example, customer satisfaction, perceived value, service quality, commitment and attitude (de Matos & Rossi, 2008). Studies have found that people depend on WOM to make various buying decisions, including the purchase of new products (Godes and Mayzlin, 2004; Arndt, 1967a), books (Chevalier and Mayzlin, 2006), movies (Liu, 2006; Moon et al., 2010), food-related products (Quinton and Harridge-March, 2010), and various services (Bansal and Voyer, 2000; de Matos et al., 2009).

Considerable research has been directed at better understanding the cause, development and outcome of WOM. The existing literature can be classified into four streams. The first focuses on the reasons why consumers spread positive or negative word about products and services they have experienced. That research reports that factors such as extreme satisfaction or dissatisfaction (Anderson, 1998; Bowman & Narayandas, 2001; Dichter, 1966; Maxham & Netemeyer, 2002; Richins, 1983; Yale, 1987), commitment to the firm (Dick & Basu, 1994), length of the relationship with the firm (Wangenheim & Bayon, 2004), and novelty of the product (Bone, 1992) drive such behaviors. In this thesis, these factors have been reviewed and selected for the WOM valence models.

The second stream aims to better understand information-seeking behaviors, or more specifically, under what circumstances consumers rely on WOM communications more than on other sources of information to make a purchasing decision. Consumers with little expertise in a product category (Furse, Punj, & Stewart, 1984; Gilly, Graham, Wolfinbarger, & Yale, 1998), who perceive a high risk in decision-making (Bansal & Voyer, 2000; Kiel & Layton, 1981), or who are deeply involved in the purchasing decision (Beatty & Smith, 1987) are more likely to seek the opinions of others for product advice.

Studies in the third stream examine why certain personal sources of information exert more influence than others. Researchers have identified factors such as source expertise (Bansal & Voyer, 2000; Gilly et al., 1998), tie strength (Brown & Reingen, 1987; Frenzen & Nakamoto, 1993), demographic similarity (Brown & Reingen, 1987), and perceptual affinity (Gilly et al., 1998) as important antecedents of WOM influence.

The fourth stream study the modeling of WOM volume based on one network topology which is the branching process, focusing on e-mail communication WOM activities (e.g. van der Lans et al., 2010; ribarren, and Moro, Esteban, 2011; Jankowski et al. 2012; Antoneli, et al., 2013). This research built on this concept of modeling the volume of WOM in viral marketing through network topology models while using complex network topologies other than the aforementioned simple network topology (branching) and use data crawled from social networking sites other than emails so as to contribute to the current literature.

## 2.1.5 PREVIOUS RESEARCH ON THEORETICAL FRAMEWORKS AND MATHEMATICAL MODELING OF WOM AND EWOM

Theoretically, based on Kozinets et al (2010), there are three models currently coexisting regarding WOM marketing, and each pertains to different circumstances. They are The Organic Interconsumer Influence Model, The Linear Marketer Influence Model and The Network Coproduction Model.

The Organic Interconsumer Influence Model represents the traditional offline WOM that the communication was from person to person in offline scenarios;

The Linear Marketer Influence Model could represent both EWOM and WOM marketing. E-mail based EWOM marketing campaigns is an example of EWOM marketing using the Linear Marketer Influence Model. Moreover, there is one and only one type of mathematical model currently existing for predicting the spread of EWOM in an email WOM campaign, which is the tree topology model firstly from Van der Lans et al. (2010). Thus Van der Lans (2010) tree topology model is the first mathematical topology model representing the theoretical Linear Marketer Influence Model. There have been several similar tree topology models developed since, and they were all tree topology models using email EWOM marketing (such as Iribarren and Moro,

2011).

The final model named the Network Coproduction Model mainly represents EWOM marketing. An example using the Network Coproduction Model is the social network EWOM marketing (viral marketing) and there has been no mathematical model so far to predict the EWOM volume using the Network Coproduction Model. This thesis will be the first research on developing mathematical model for predictions on EWOM volume in social networks corresponding the Network Coproduction Model.

#### 2.1.5.1 THE ORGANIC INTERCONSUMER INFLUENCE MODEL

Early scholarship established WOM as a significant social force, influencing early marketing thought and practice. For example, Ryan and Gross's (1943) diffusion study suggested that conversations among buyers were more important than marketing communications in influencing adoption (see also Rogers 1962). This research refer to the earliest and simplest understanding of consumer WOM as a model of organic nter-consumerinfluence. These inter-consumer communications pertain to the exchange of product and brand-related marketing messages and meanings. In this model, WOM is "organic" because it occurs between one



consumer and another without direct prompting, influence, or measurement by marketers. It is motivated by a desire to help others, to warn others about poor service, and/or to communicate status (Arndt 1967; Engel, Kegerreis, and Blackwell 1969; Gatignon and Robertson 1986). Views of WOM in this model assume that WOM occurs naturally among consumers when marketers perform their job of developing market innovations and performing effective product notification through advertising and promotions (Bass 1969; Whyte 1954).

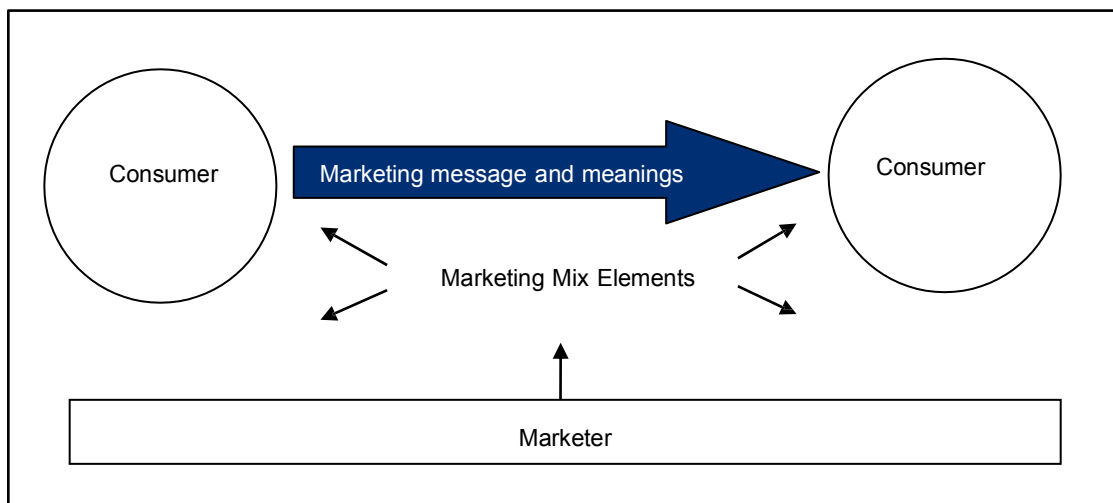


Figure 4 The Organic Inter-consumer Influence Model

#### 2.1.5.2 THE LINEAR MARKETER INFLUENCE MODEL AND TREE TOPOLOGY MODEL

As marketing scholarship and practice advanced, theories of WOM began to emphasize the importance of particularly influential consumers in the WOM process (e.g., Feick and Price 1987; King and Summers 1976). Accordingly, it was in marketers' interests to identify and attempt to influence these influential, respected, credible, WOM-spreading consumers. This understanding now incorporates an active attempt by the marketer to influence consumer WOM through the use of traditional means, such as advertising and promotions. Therefore, this stage is referred to as a model of linear influence. Occurring during the "cultural engineering" marketing practices of the post-World War II era, which were formed to overcome increasingly resistant buyers (Holt 2002), some consumers were viewed as potential "opinion leaders" who smart marketers could target and influence. Marketers would now be able to work through "the friend who recommends a tried and trusted product" rather than the "salesman who tries to get rid of merchandise" (Dichter 1966, p. 165). Accurate, "realistic information" in marketing was important in these early conceptions because the opinion leader was assumed to transmit marketing messages more or less faithfully, without substantially altering them or having

them altered by ongoing communications with other consumers (Brooks 1957; Engel, Kegerreis, and Blackwell 1969; Katz and Lazarsfeld 1955).

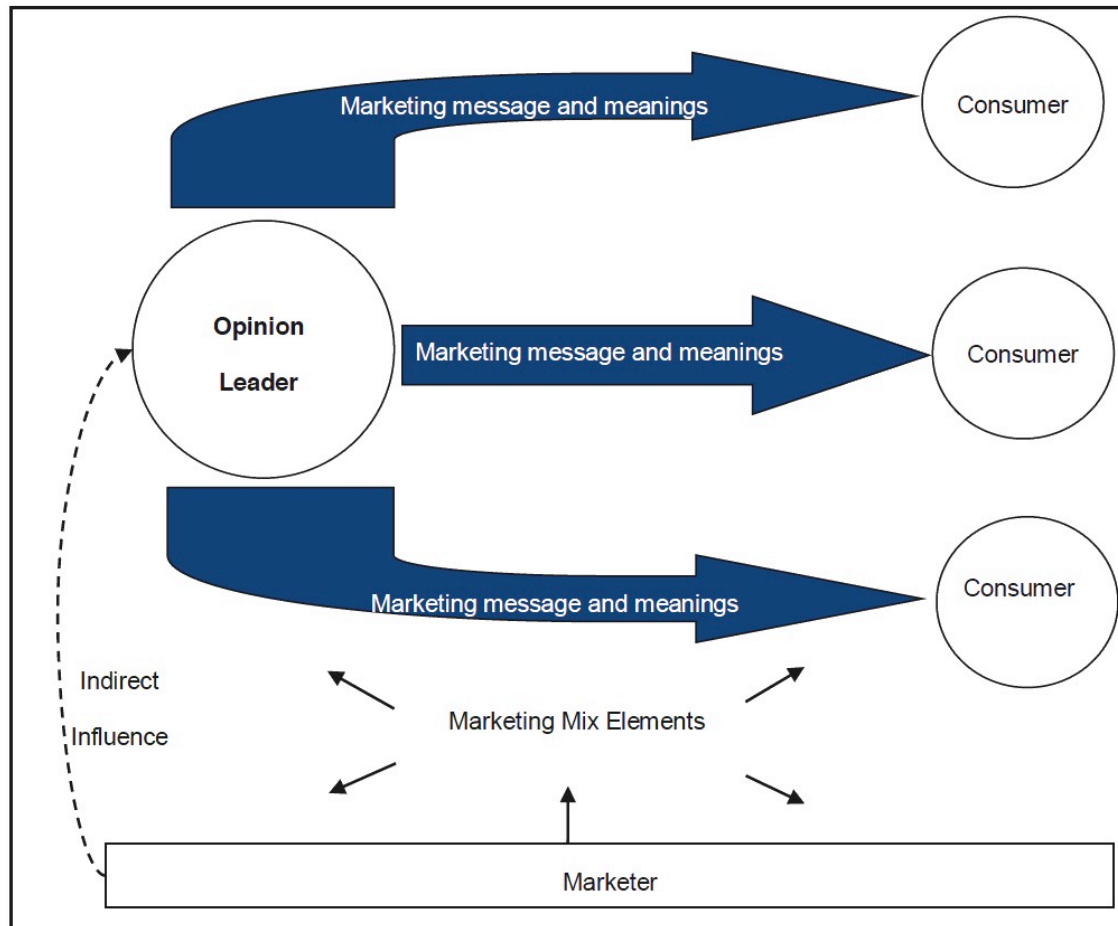


Figure 5 The Linear Marketer Influence Model

Corresponding to this theoretical model, there is the tree topology model named viral branching model developed by Van der Lans et al. (2010). A branching process model is an example of a network topology model – Tree Topology. Using tree topology means that the viral Marketing WOM volume increase is treated as a Branching Process of a tree.

Branching process models have proven to be very useful in describing the spread of viruses theoretically, they have not been applied to real empirical process data until van der Lans (2010). The reason for this is that, similar to the diffusion of products, the process of the actual spread of viruses is typically not observed. Interestingly, in viral marketing campaigns, marketers can observe the actual spread of information across customers, and branching processes might therefore be a promising tool to describe and predict the reach of these campaigns, thus the research of van der Lans (2010) focused on the modeling of WOM spread with branching process models which belong to a type of topology models- tree topology models.

The branching process in terms of information diffusion may be basically described as a process where an individual may spread the information to a number of consequents. Starting from a number of seeds understood as the first generation the information is forwarded towards next generations, creating a tree of information traversal. The information diffusion ends when there will be no further infections, that means reaching the all of the susceptible users. The nature of the branching process, especially the fact that it is not based on time but on generations, makes the whole process a bit harder to interpret on a time basis, because the number of users infected in a particular generation changes over time. And as the basic equations of the branching process are calculating

the number of infected in the next generation basing on the previous one, the chance to estimate the parameters while the campaign is on-going is very weak, unless there exists a certainty that the number of infected users in previous generations would not change, which is rather unlikely in real campaigns. That results in constant underestimation of the overall number of infected users.

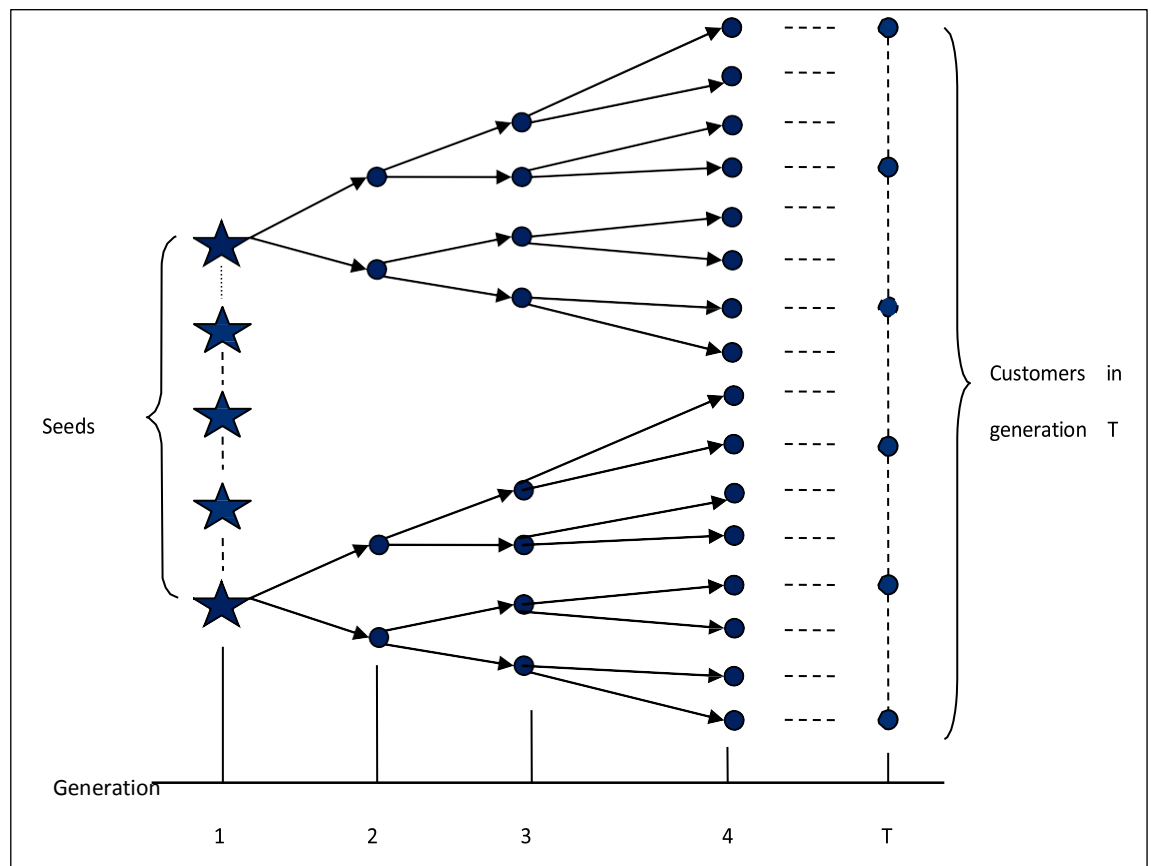


Figure 6 Spread of a Message in a Viral Marketing Campaign as a Branching Process

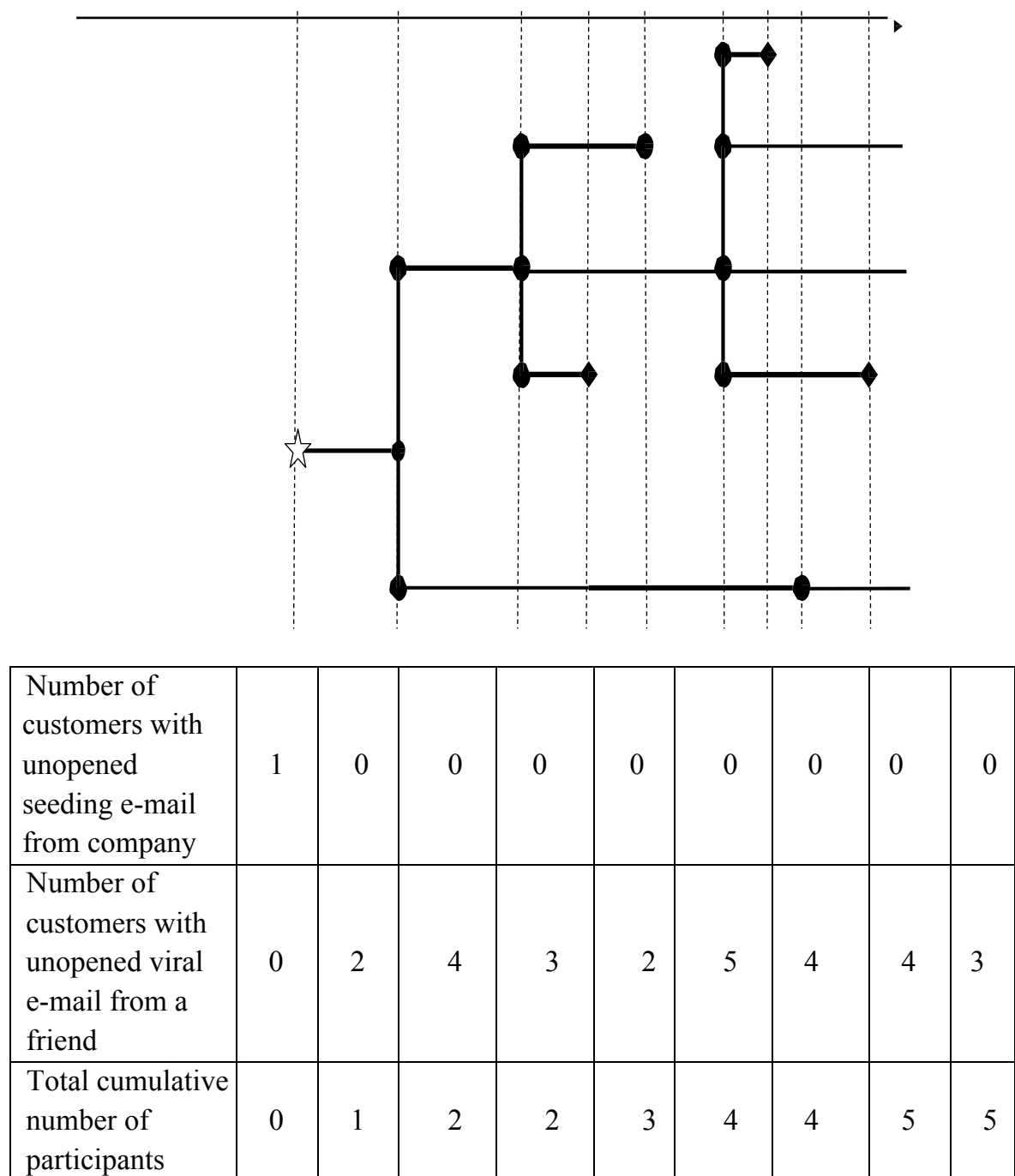


Figure 7 Branching Process by Van Der Lans (2010)

At  $t_0$  customer A is invited to the viral marketing campaign, in this case through receiving a seeding e-mail sent by the company (☆), but this could

also be because of a banner or advertising. Hence,  $M(t_0) = 1$ . At  $t_1$  customer A participates in the viral campaign (indicated by  $\bullet$ ) ( $N(t_1) = 1$ ) after opening the e-mail ( $M(t_1) = 0$ ) and decides to forward the message to two friends, B and C ( $V(t_1) = 2$ ). At  $t_2$ , customer B participates in the campaign ( $N(t_2) = 2$ ) after opening the e-mail from friend A and forwards it to three new friends: D, E, and F ( $V(t_2) = V(t_1) - 1 + 3 = 4$ ). Subsequently, at  $t_3$ , customer F opens the e-mail and is not interested in the campaign (indicated by  $\circ$ ), i.e.,  $V(t_3) = V(t_2) - 1 = 3$ , after which customer D opens the e-mail ( $V(t_4) = V(t_3) - 1 = 2$ ) and participates in the campaign ( $N(t_4) = N(t_3) + 1 = 3$ ) but does not forward the message to friends. At  $t_5$ , customer E opens the e-mail, starts participating in the campaign, and forwards the message to four friends: G, H, I, and J; i.e.,  $N(t_5) = 4$  and  $V(t_5) = V(t_4) - 1 + 4 = 5$ . At  $t_6$ , customer G opens the e-mail from friend E but is not interested in the campaign, ( $V(t_6) = 4$ ). Then at  $t_7$ , customer C opens the e-mail and participates in the campaign ( $N(t_7) = 5$ ) and forwards a message to friend K ( $V(t_7) = V(t_6) - 1 + 1 = 4$ ). Finally, at  $t_8$ , customer J opens the e-mail but does not participate; hence,  $V(t_8) = 3$  and  $M(t_8)$  and  $X(t_8)$  do not change (Van Der Lans, 2010).

#### 2.1.5.3 THE NETWORK COPRODUCTION MODEL AND COMPLEX NETWORK TOPOLOGY MODEL

The next stage of understanding is the more recent, and though it coincides with the development and recognition of the importance of the Internet, it is not limited to this domain. Marketers have become interested in directly managing WOM activity through targeted one-to-one seeding and communication programs, with the Internet allowing unprecedented new levels of management and measurement of these campaigns and new professional organizations allowing the efficient development and diffusion of WOM knowledge.

Marketing scholarship has evolved from a transaction orientation to one based on relationships (Vargo and Lusch 2004), with increasing importance placed on the role of consumer networks, groups, and communities (Cova and Cova 2002; Hoffman and Novak 1996; Muniz and O'Guinn 2001). Consumers are regarded as active coproducers of value and meaning, whose WOM use of marketing communications can be idiosyncratic, creative, and even resistant (Brown, Kozinets, and Sherry 2003; Kozinets 2001; Muñiz and Schau 2005; Thompson and Sinha 2008). Thus, WOM communications are coproduced in consumer networks. There are two distinguishing characteristics of this new model of understanding. First is marketers' use of



new tactics and metrics to deliberately and directly target and influence the consumer or opinion leader. Second is the acknowledgment that market messages and meanings do not flow unidirectionally but rather are exchanged among members of the consumer network.

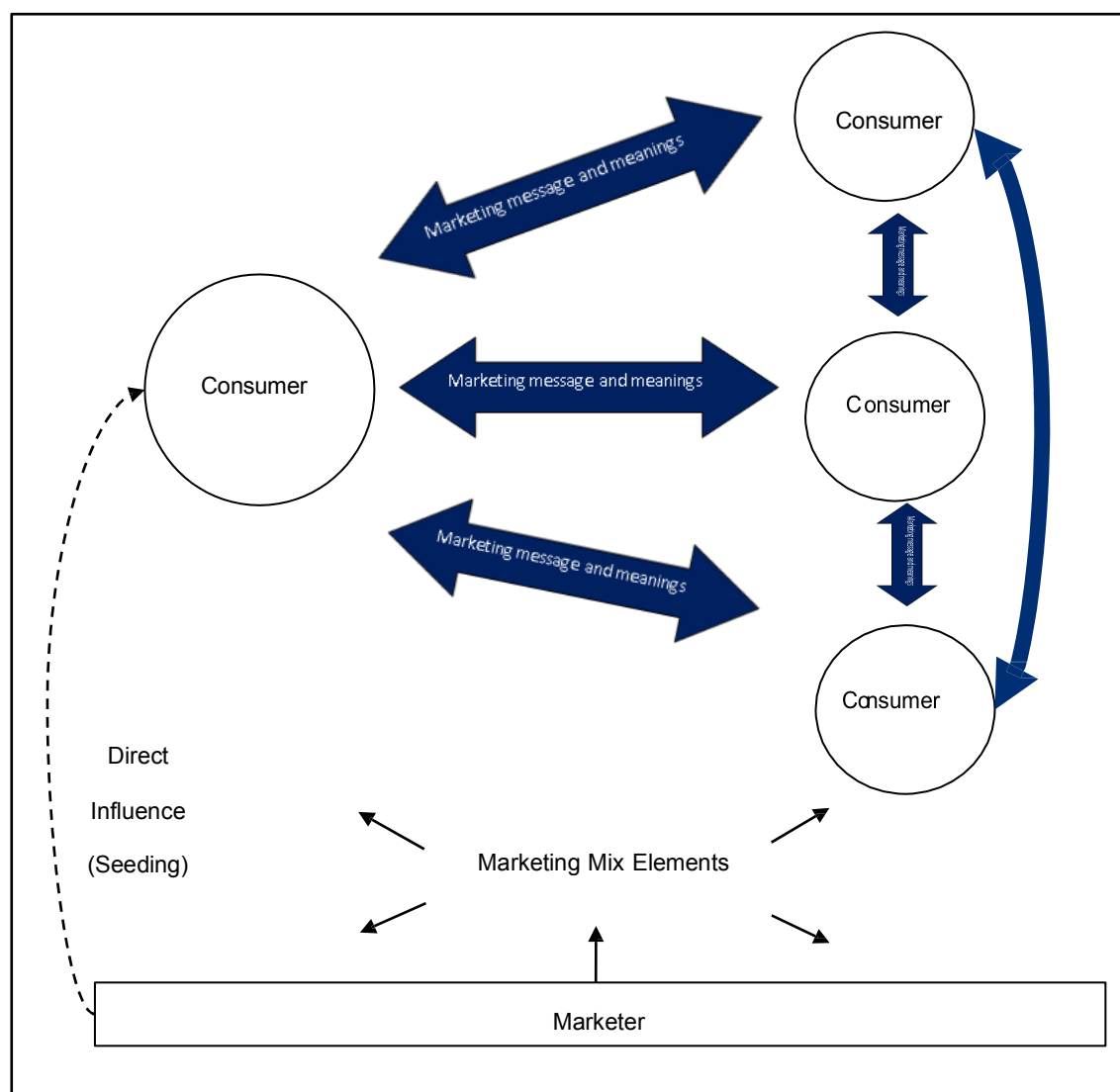


Figure 8 The Network Coproduction Model

The mathematical model for predicting WOM volume to be developed in this thesis corresponds to this theoretical model. There has been no mathematical model developed using this theoretical model yet. This model emphasizes the interrelationships among social networks, unlike the linear relationships in The Linear Marketer Influence Model. In this thesis, complex network topology model would be developed and tested as the first mathematical model for this nonlinear Network Coproduction Model.

## 2.2 THE CAUSE, DEVELOPMENT AND OUTCOME OF WOM MARKETING: WITH PARTICULAR REFERENCE TO THE MODELING OF WOM VOLUME

### 2.2.1. THE CAUSE OF WOM VOLUME

Desire for social interaction, concern for other customers, the motivation for economic incentives, and the potential to enhance one's own self-worth have been established and accepted as primary motivations for engaging in eWOM (Hennig-Thurau et al., 2004). While "The marketplace is an important domain for everyday helping behavior" (Price et al., 1995, p. 262), "our willingness to share is motivated by our basic human need to be helpful by giving advice" (Smith et al., 2007, p. 387).

It is well-established in the literature that people perceive consumer recommendations as more trustworthy than those of experts (Huang and Chen, 2006). In their influential work, Feick and Price (1987) identified the concept of a "market maven" who is an individual with general marketplace knowledge or expertise. A market maven's influence is in direct contrast to an opinion leader with product-specific knowledge or

expertise. “Research suggests that consumers are able to identify market mavens, use them in making consumption decisions, and distinguish them from individuals with product-based expertise” (Feick and Price, 1987, p. 94). With an ability to differentiate between expert and consumer online recommendations (Huang and Chen, 2006), it is with confidence and common enjoyment that people seek out valuable information (Smith et al., 2007). Therefore, online consumers have confidence in the validity of consumer-provided information online, enjoy interacting with other consumers online, and rely on a network of consumers with marketplace knowledge or expertise to guide their purchase decisions.

| Motivation       | Key studies  | Social network site studies   |
|------------------|--|---|
| Social benefits  | Hennig-Thurau et al. (2004): social benefits<br>Daugherty et al. (2008): social function | Nadkarni and Hofmann (2012): need to belong<br>Chu and Kim (2011): trust, normative influence |
| Self-enhancement | Hennig-Thurau et al. (2004): extraversion/self-enhancement<br>Daugherty et al.           | Nadkarni and Hofmann (2012): need for self presentation                                       |

|                                     |   |  |
|-------------------------------------|---|--|
|                                     | (2008):   |  |
| Extraversion                        | Hennig-Thurau et al.<br>(2004):<br>extraversion/self-enhancement  |  |
| Dissonance<br>reduction<br>Altruism | Daugherty et al.<br>(2008): ego-defensive<br>Hennig-Thurau et al.<br>(2004): concern for<br>other consumers |  |
| Economic<br>incentives              | Hennig-Thurau et al.<br>(2004): economic<br>incentives  |  |

Table 6 Motivations of WOM

Note: The “Motivation” column shows the present study’ categorization of eWOM motivation constructs for creating eWOM volume based on literature review. The location of the citations indicates the motivation and the context studied. The term following each citation is the specific term used in that study.

Hennig-Thurau et al.’s (2004) analysis showed that the frequency of platform visits and comment writing are correlated with different sets of motivations. This hints that individual eWOM behaviors might correspond to different sets of motivations, which is likely in the context

of media choice. Schindler and Bickart (2005) argued that consumers' choice of an online platform for reading eWOM varies based on the consumer's motivation. Since posters are also readers, the type of site is likely to be important when posters are deciding where to post reviews (Bronner and de Hoog, 2011). The eWOM content and where to post the eWOM are intrinsically linked (Wilson et al., 2012).

Based on a review of 42 academic studies on Facebook use, Nadkarni and Hofmann (2012) concluded that the need to belong and the need for self-presentation are the primary motivations for using Facebook. Chu and Kim (2011) argued that a key motivation for engaging in eWOM on social network sites may be establishing and maintaining personal social networks. Wilson et al. (2012) also found that posting on social network sites is positively correlated to wanting to share experiences, especially positive ones, with friends.

### *Seeding strategy*

Marketers may control is how to start the viral campaign in social website—what usually is referred to as the “seeding strategy.” A seeding strategy involves determining how many initial consumers (“seeds”) are needed to disseminate a viral message to and what types of consumers to choose as seeds.

According to Hinz et al. (2011), to achieve successful WOM campaign, firms must consider four critical viral marketing success factors: (1) content, in that the attractiveness of a message makes it memorable (Berger and Milkman 2011; Berger and Schwartz 2011; Gladwell 2002; Porter and Golan 2006); (2) the structure of the social network (Bampo et al. 2008); (3) the behavioral characteristics of the recipients and their incentives for sharing the message (Arndt 1967); and (4) the seeding strategy, which determines the initial set of targeted consumers chosen by the initiator of the viral marketing campaign (Bampo et al. 2008; Kalish, Mahajan, and Muller 1995; Libai, Muller, and Peres 2005). This last factor is of particular importance because it falls entirely under the control of the initiator and can exploit social characteristics (Toubia, Stephen, and Freud 2010) or observable network metrics.

The conventional wisdom adopts the influentials hypothesis, which states that targeting opinion leaders and strongly connected members of social networks (i.e., hubs) ensures rapid diffusion Iyengar, Van den Bulte, and Valente 2011). However, recent findings raise doubts. Van den Bulte and Lilien (2001) show that social contagion, which occurs when adoption is a function of exposure to other people's knowledge, attitudes, or behaviors (Van den Bulte and Wuyts 2007), does not

necessarily influence diffusion, and yet it remains a basic premise of viral marketing. Such contagion frequently arises when people who are close in the social structure use one another to manage uncertainty in prospective decisions (Granovetter 1985). However, in a computer simulation, Watts and Dodds (2007) show that well-connected people are less important as initiators of large cascades of referrals or early adopters. Their finding, which Thompson (2008) provocatively summarizes by implying “the tipping point is toast,” has stimulated a heated debate about optimal seeding strategies, though no research offers an extensive empirical comparison of seeding strategies. Van den Bulte (2010) thus calls for empirical comparisons of seeding strategies that use sociometric measures (i.e., metrics that capture the social position of people). In response, Hinz et al (2011) undertook an empirical comparison of the success of different seeding strategies for viral marketing campaigns and identify reasons for variations in these levels of success and suggest that seeding to well-connected people is the most successful approach because these attractive seeding points are more likely to participate in viral marketing campaigns.



## 2.2.2 NETWORK TOPOLOGY AND THE DEVELOPMENT OF WOM VOLUME

Since the early work of Katz and Lazarsfeld (1955) there has been great interest in how WOM drives consumer demand, public opinion, and product diffusion (Brown and Reingen 1987, Godes and Mayzlin 2004, Aral et al. 2009) and how firms can create broad, systematic propagation of WOM through consumer populations (Phelps et al. 2004, Mayzlin 2006, Dellarocas 2006, Godes and Mayzlin 2009). Many campaigns target “influential” individuals who are likely to propagate organic WOM most broadly (Katz and Lazarsfeld 1955, Watts and Dodds 2007, Goldenberg et al. 2009), using referral programs to create incentives for them to spread the word (Biyalogorsky et al. 2001). Others use observational evidence on viral campaigns to inform viral branching models of WOM diffusion (Van der Lans et al. 2010). However, to this point, studies of the dynamic modeling of WOM diffusion are limited to branching models, the discussions of other topology models are absent from the literature on viral marketing.

As discussed in section 2.1.5.3, there exists one type of mathematical topology model which is the tree topology model developed by Van der

Lans et al. (2010) and it corresponds with the theoretical Linear Marketer Influence Model. Thus this section will briefly discuss the existing viral branching models of WOM diffusion, and then explore more topology models that are potentially appropriate for developing WOM volume models.

#### 2.2.2.1 NETWORK TOPOLOGY THEORY AS CONCEPTUAL BASE FOR WOM VOLUME

Insights from epidemics about the spread of viruses are useful to understand and model the spread of marketing messages in viral marketing campaigns. In epidemics, both aggregate- and disaggregate-level models have been developed to describe the spread of viruses (Bartlett 1960). Aggregate-level or diffusion models assume an underlying infection process, and the corresponding model parameters are inferred from the total number of infected individuals over time. Based on these insights, Bass (1969) developed his famous diffusion model and assumed adoption to depend on two forces: one that is independent of previous adoptions and one that depends positively on previous adoptions.

As the number of customers in viral marketing campaigns (i.e., adopters)

is also influenced by these two forces, the Bass model should be able to describe the spread of information during viral marketing campaigns. However, there are two important reasons why the Bass model does not optimally describe the viral marketing process. First, it assumes a specific process but does not include actual information on this process at the individual level. Such information becomes readily available in viral marketing campaigns and can be used to describe the process accurately at the aggregate level. Second, the Bass model assumes that every customer who has adopted the product increases the probability of others adopting in each time period after adoption. However, in viral marketing campaigns, customers only influence each other right after the viral message being forwarded by other friends.

Disaggregate-level or branching process models (Athreya and Ney 1972, Dorman et al. 2004, Harris 1963) may alleviate these two limitations as parameters are estimated based on individual-level information, and they assume that customers only influence each other right after infecting a fixed number of others. Based on their theories, van der Lans (2010) came up with branching models to describe the spread of WOM (the development of WOM volume).

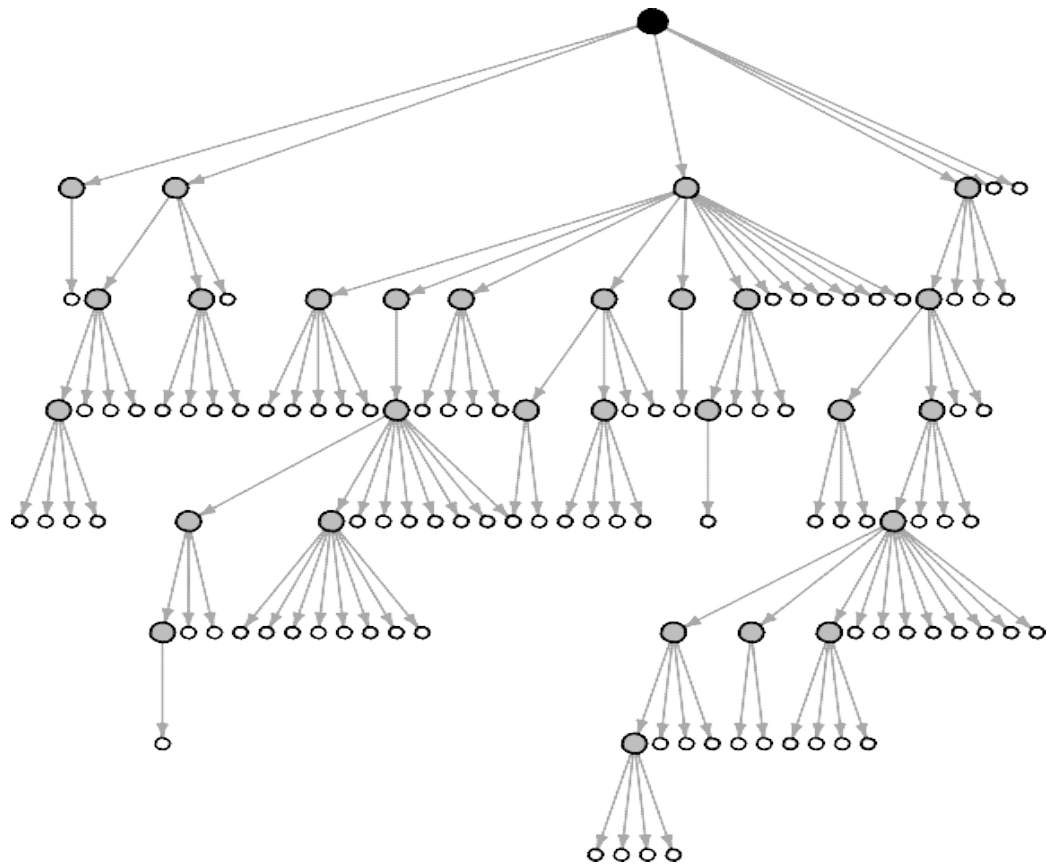


Figure 9 Branching Process

Notes: The viral messages diffusion graph (tree topology) of an email communication viral marketing campaign that a set of 7,118 disconnected cascades like this one observed in Spain. Its 122 nodes (represented by dots) are grouped in 8 generations (horizontal layers) that stem from the generation zero node at the top (*Seed* node, black) and grow through a branching process driven by the active nodes (gray) in each generation. Its tree-like structure is devoid of closed paths or triangles for a clustering coefficient  $C = 0$  (Iribarren, 2011).

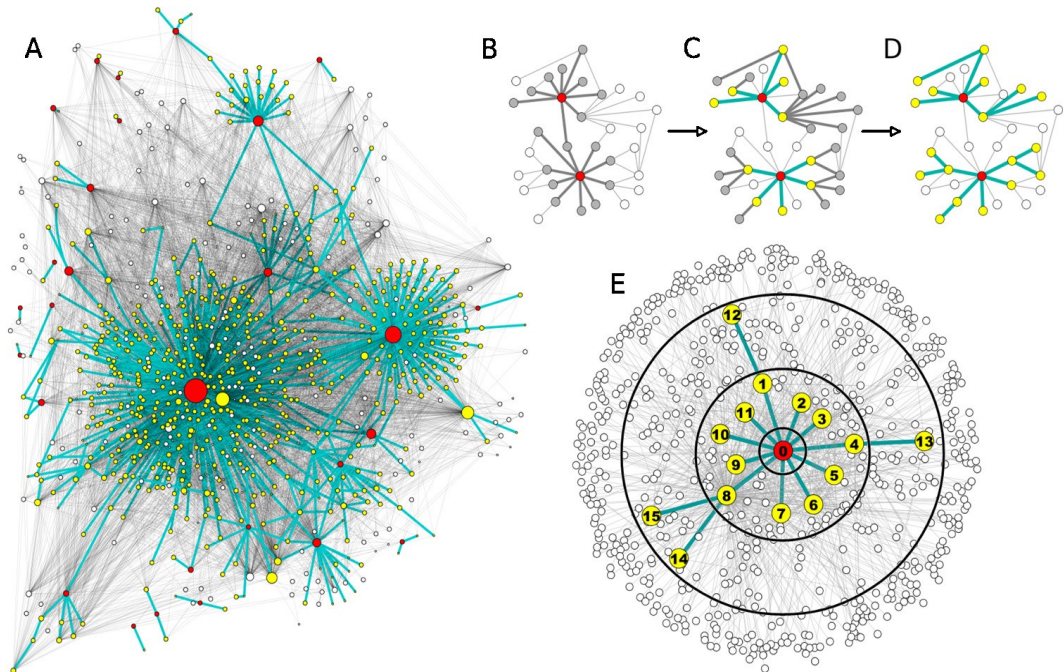


Figure 10 Visualization of an example retweet network emergent from the message propagation on the followers network (Morales et al., 2014).

Notes: (A) Subgraph of the retweet networksuperimposed to the corresponding followers network, from the #SOSInternetVE dataset. In the figure a subset of 1000 random nodes (yellow and red) are presented. The node size is proportional to the respective in degree on the followers network; (B–D) example of the formation of the retweet network from independent retweet cascades on an artificial followers network; (B) when two users post independent messages which are received by their

followers; (C) when some users retweeted the message and this message arrives to their followers; (D) the final shape of the cascades on the network, compound only by the activated nodes connected by the green links. The white nodes and gray links represent the rest of the substratum (followers network) who did not activate; and (E) the schema of a single cascade. The black circles determine the cascade layers (Morales et al., 2014).

Information diffusion travels through social connections thereby depending on the properties of the social networks where it spreads. For example, simulations on synthetic scale-free networks showed that if information owed through every social connection the epidemic threshold would be significantly lowered to the extent that it could disappear (Newman, 2002; Golub, and Jackson, 2010), so that any rumor, virus or innovation might reach a large fraction of individuals in the population no matter how small the probability of being infected. Results of previous studies predict that there is a strong interplay between network structure and the spreading process (e.g. Newman, 2003; van der Lans, 2101).

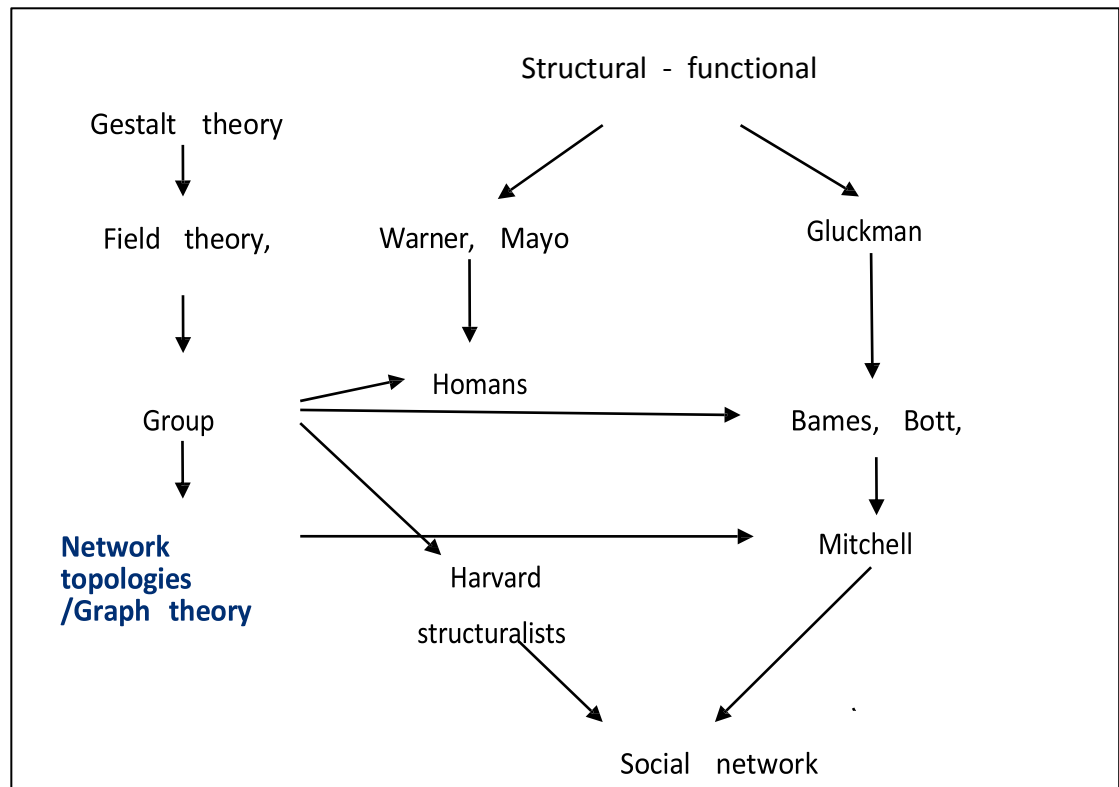


Figure 11 Previous Research on Social Network Topology Studies

Network topologies models focus on problems that can be represented as a network graph (graph theory) or a network such as logistic problems, network design problems, and project management problems. Several optimization problems on networks are computationally very demanding.

A number of diverse strands have shaped the development of present-day social network analysis. These strands have intersected with

one another in a complex and fascinating history, sometimes fusing and at other times diverging onto their separate paths (Freeman, 2004). A clear lineage for the mainstream of social network analysis for the mainstream of social network analysis can, nevertheless, be constructed from this complex history. In this lineage there are three main traditions: the sociometric analysis, who worked on small groups and produced many technical advances using the methods of network topologies; the researchers of the 1930s, who explored patterns of interpersonal relations and the formation of 'cliques'; and the social anthropologies, who built on both of these strands to investigate the structure of 'community' relations in tribal and village societies. These traditions were eventually brought together in the 1960s and 1970s, when the contemporary social network analysis was forged.

The 'gestalt' tradition in psychology, associated with the work of Wolfgang Kohler (1925), stresses the organised patterns are regarded as 'wholes' or systems with properties distinct from those of their 'parts' and that, furthermore, determine the nature of those parts. The individual objects that people perceive, for example, are seen in particular ways because they are, literally, preconceived within the complex and organised conceptual schemes of human mind. The objects of the world are not perceived independent of these mental schemes but are, in a



fundamental sense, constituted by them. Social psychology is this research tradition has stressed the social determination of these conceptual schemes and has, therefore, emphasised the influence of group organisation and its associated social climate on individual perceptions.

Many of the leading gestalt theorists fled from Nazi Germany during the 1930s and settled in the United States, where Kurt Lewin, Jacob Moreno (who had migrated there in 1925) and Fritz Heider became prominent, though rather different, exponents of a gestalt-influenced social psychology. Lewin established a Research centre at the Massachusetts Institute of Technology, later moving it to Michigan, and this centre became the focus of research on social perception and group structure in the approach called 'group dynamics'. Moreno, on the other hand, explored the possibility of using psychotherapeutic methods to uncover the structure of friendship choices. Using experimentation, controlled observation and questionnaires, he and his colleagues aimed to explore the ways in which people's group relations serve as both limitations and opportunities for their actions and, therefore, for their personal psychological development. Although the word 'sociometric' is particularly associated with Mereno, it is an apt description of the general style of research that arose from the gestalt tradition.

Moreno's work was firmly rooted in a therapeutic orientation towards interpersonal relations, reflecting his early medical training and psychiatric practice in Vienna. His aim, elaborated in a major book (Moreno, 1934; And see Bott, 1928) and in the founding of a journal (Sociometry, founded in 1937), as to investigate how psychological well-being is related to the structural features of what he termed 'social configurations' (Moreno and Jennings, 1938). These configurations are the results of the concrete patterns of interpersonal choice, attraction, repulsion, friendship and other relations in which people are involved, and they are the basis upon which large-scale 'social aggregates', such as the economy and the state, and sustained and reproduced over time. Moreno's concern for the relationship between small-scale interpersonal configurations and large-scale social aggregates is a very clear expression of some of the leading ideas of classical German sociology, most notably those developed in the works of Weber, Tonnies, and Simmel. Indeed, the latter's so-called formal sociology directly anticipate many sociometric concerns (Simmel, 1908; Aron, 1964).

Moreno's chief innovation was to devise the 'sociogram' as a way of representing the formal properties of social configurations. These could, he held, be represented in diagrams analogous to those of spatial

geometry, with individuals represented by 'points' and their social relationships to one another by 'lines'. This idea is now so well established and taken for granted that its novelty in the 1930s is difficult to appreciate. Before Moreno, people had spoken of 'webs' of connection, the 'social fabric' and, on occasion, of 'networks' of relations, but no one had attempted to systematize this metaphor into an analytical diagram.

For Moreno, social configurations had definite and discernible structures, and the mapping of these structures into a sociogram allowed a researcher to visualise the channels through which, for example, information could flow from one person to another and through which one individual could influence another. Moreno argued that the construction of sociograms allowed researchers to identify leaders and isolated individuals, to uncover asymmetry and reciprocity, and to map chains of connection. One of his principal sociometric concepts was that of the sociometric 'star': the recipient of numerous and frequent choices from others and who, therefore, holds a position of great popularity and leadership. For Moreno, the concept of the star pointed to an easily visualised picture of the relations among group members. For example, person A is the recipient of friendship choices from all the other members of a group, yet A is the recipient of friendship choices only to

person B and C. A is, therefore, the star of attraction within the group. This work has some influence on community research (Lundberg, 1936; Lundberg and Steele, 1938) and became an important area of research in the sociology of education (Jennings, 1948; Evans, 1962).

Lewin's early work on group behaviour is to be seen as determined by the field of social forces in which the group is located (Lewin, 1936). A social group, he argued, exists in a field - a social 'space' that comprises the group together with its surrounding environment. But the environment of the group is not seen as something purely external to and independent of the group. The environment that really matters to group members is the perceived environment. The perceived environment is what writers in the symbolic interactionist tradition have called the 'definition of the situation', and its social meaning is actively constructed by group members on the basis of their perceptions and experiences of the contexts in which they act. The group and its environment are, therefore, elements within a single field of relations. The structural properties of this social place, Lewin argued, can be analysed through the mathematical techniques of topology and set theory (Lewin, 1951). The aim of 'field theory' is to explore, in mathematical terms, the interdependence between group and environment in a system of relations (Martin, 2003), a view that brought Lewin close to later developments in

general system theory (i.e. Buckley, 1967, for an application of this framework to sociology.)

In a topological approach, the social field is seen as comprising points connected by 'paths'. The points, as in sociogram, represent individual persons, their goals, or their actions, while the paths represent the interactional or casual sequences that connect them. The field model, therefore, describes causal and interactional interdependences in social configurations. The paths that run between points and tie them together and the pattern of paths divide a field into a number of discrete 'regions'. Each region is separated from others by the absence of paths between them: paths run within but not between the regions. The opportunities that individuals have to move about in their social world are determined by the boundaries between different regions of the field in which they are located. The constraints imposed by these boundaries are the 'forces' that determine group behaviour. The total social field, therefore, is a field of forces acting on group members and shaping their actions and experiences.

A further strand of cognitive psychology that made a major contribution to the development of theories of social network dynamics was the work of Heider. His initial work had been on the social psychology of

attitudes and perception, and he was especially concerned with how a person's various attitudes taken by an individual are balanced in his or her mind when they do not result in a state of psychological balance, with the congruence (or lack of congruence) among attitudes to other people. He was concerned, for example, with how a person who is emotionally close to two other people might respond to any perceived conflict or hostility between them. In such a situation, there is an imbalance in the whole field of attitudes. Heider (1946) held that attitudes can be seen, at their simplest, as positive or negative. 'balance' exists among a set of attitudes when they are similar to one another in their sign: all positive or all negative. If person A likes person B, and person B likes person C, a state of balance exists only if A also likes C, as all the attitudes are then 'positive'.

## 2.2.2.2 NETWORK TOPOLOGIES AND WOM VOLUME

### DEVELOPMENT

#### 2.2.2.2.1 NETWORK TOPOLOGIES SELECTION

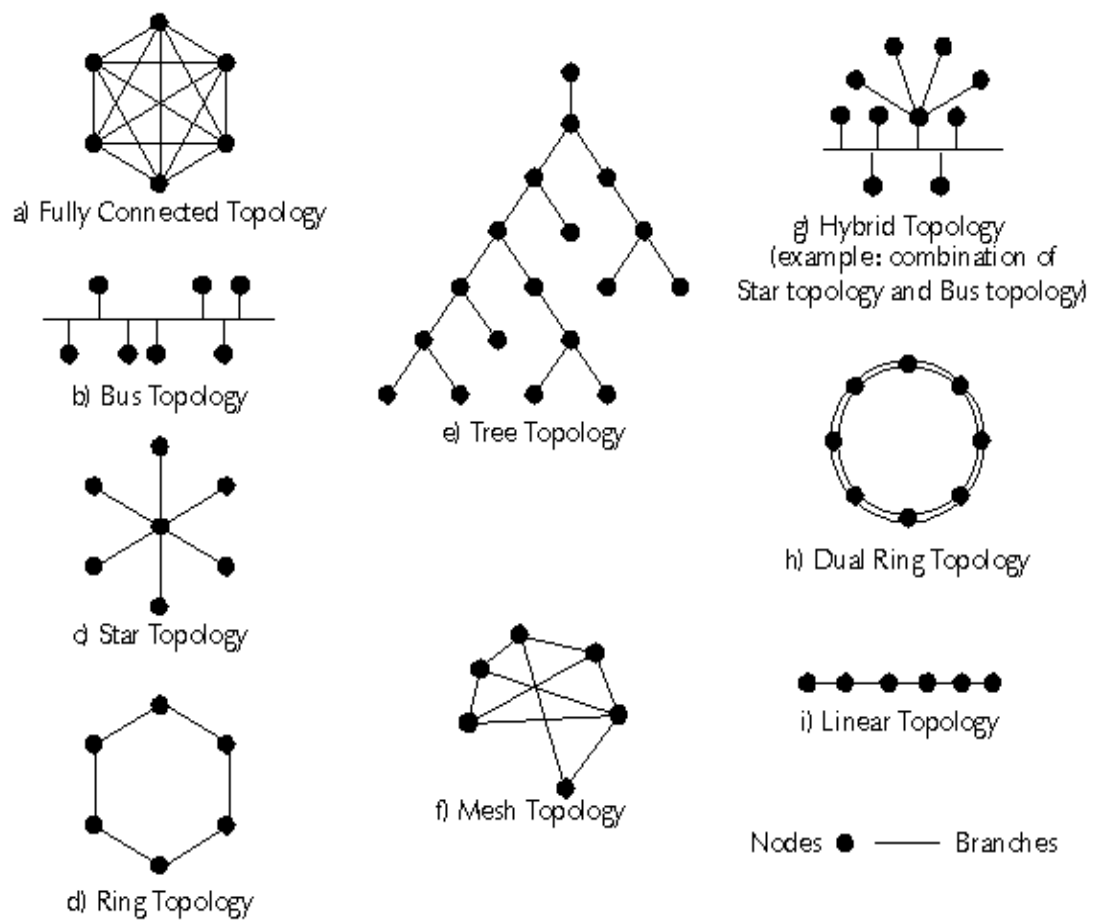


Figure 12 Network Topologies

The mathematical subject of Topology investigates objects whose characteristics are constant through distortion. Objects can be topologically equivalent while appearing physically different. There are six common types of network topologies that describe the arrangement

of the various nodes in a social network. They include bus topology network, star topology network, ring topology network, tree topology network, mesh topology network and complex network.

### *Bus Topology*

In Bus Network Topology, all nodes in the network are connected through one “backbone” that messages from one node can be seen near simultaneously spread to all other nodes on the network (Lafata, and Vodrazka, 2011). This network topology describes a situation where the information diffusion depends on one platform and limited to the number of nodes (i.e. individuals) directly subscribed to the single platform and once the platform breaks down the information diffusion fails. Thus the advantages of bus topology include that it is easy to spread the message fast and suitable and easy to use for small or temporary networks. The disadvantage is that it is not meant to be used as a stand-alone construct. This topology is not applicable for describing the whole picture of WOM volume development in social network, because it only describes a small network where everyone is online and assess information all at the same time. But it could be part of a social network structure (e.g. temporary group discussion).



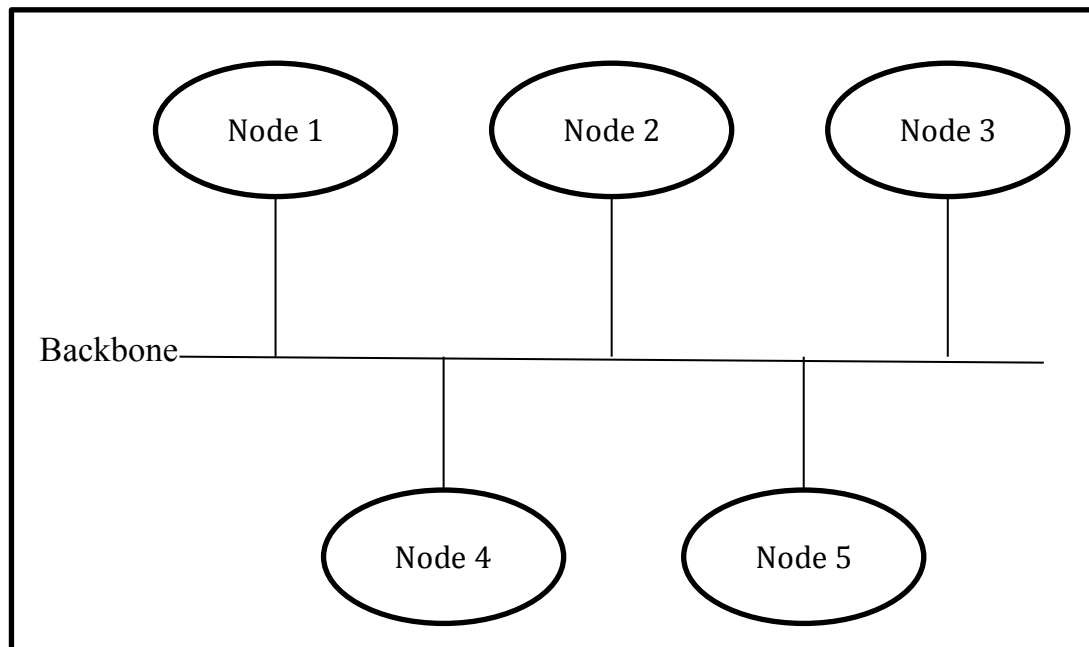


Figure 13 Bus Topology

#### *Star topology network*

In this topology a central switch or hub is used to connect all the components. The agents are not linked to each other and it does allow direct traffic between agents. The active star network has an active central node that usually has the means to prevent echo –related problems. ( Chen, Rouskas, and Dutta, 2008). This topology is not applicable for describing the whole picture of WOM volume

development in social network, because it only describes a network where everyone needs to assess or exchange information through an intermediate every time. But it could be part of a social network structure (e.g. long-distance task distribution).

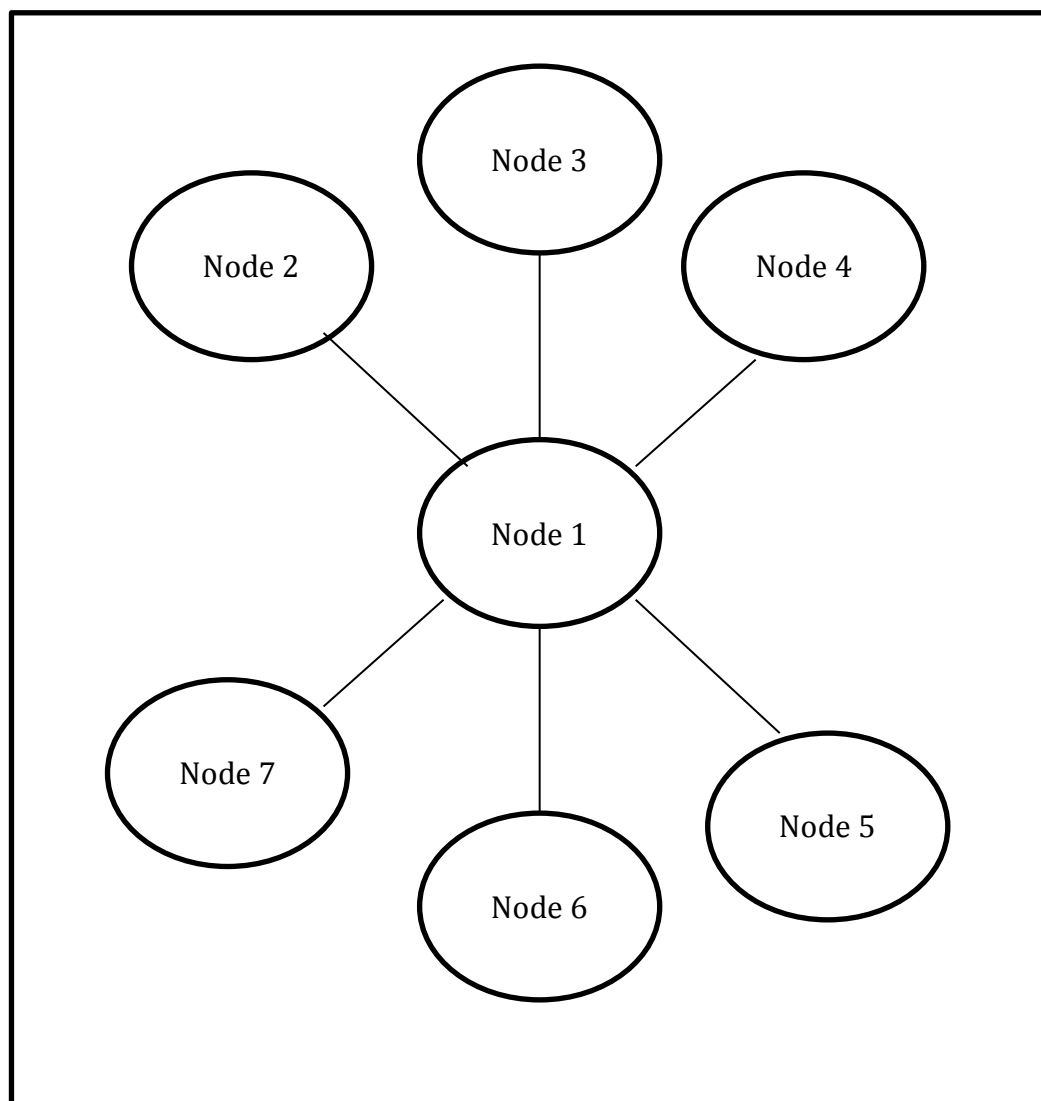


Figure 14 Star Topology

### *Ring topology network*

In this topology each node connects to exactly two other nodes that is a direct point- to- point link between two neighboring nodes forming a circular pathway for signal like a ring. Data is transferred in a sequential manner that is bit by bit.

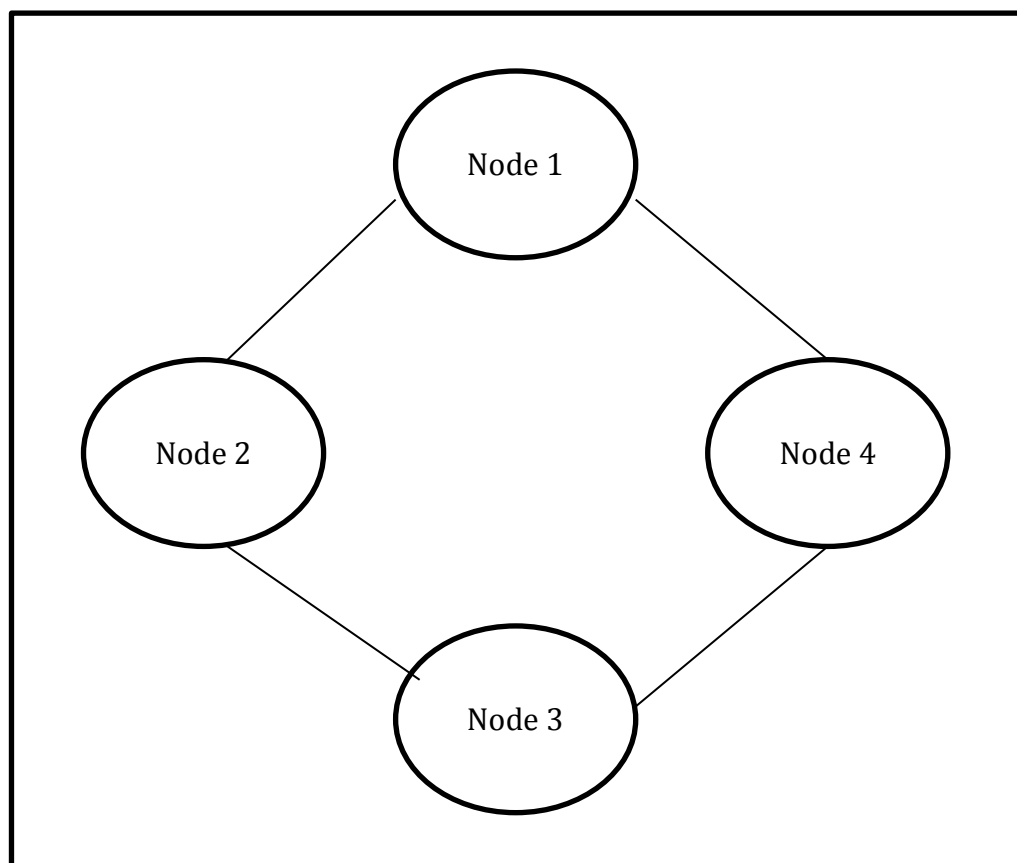


Figure 15 Ring Topology

This topology is not applicable for describing the whole picture of WOM volume development in social network, because it only describes

a network where everyone exchange information through a close ‘neighbour’. But it could be part of a social network structure (e.g. a WOM communication in a neighbourhood).

### *Tree topology network*

Tree topology networks have been applied in the literature for the modeling of WOM volume. In this topology only one route node exists between any two nodes on the network. It is also called hierarchical topology having at least three levels to the hierarchy. This section will review the tree topology and branching process in more depth and investigate the genealogical structure of continuous state branching processes in connection with limit theorems for discrete Galton-Watson trees for benchmarking the modelling of WOM volume in the methodology section.

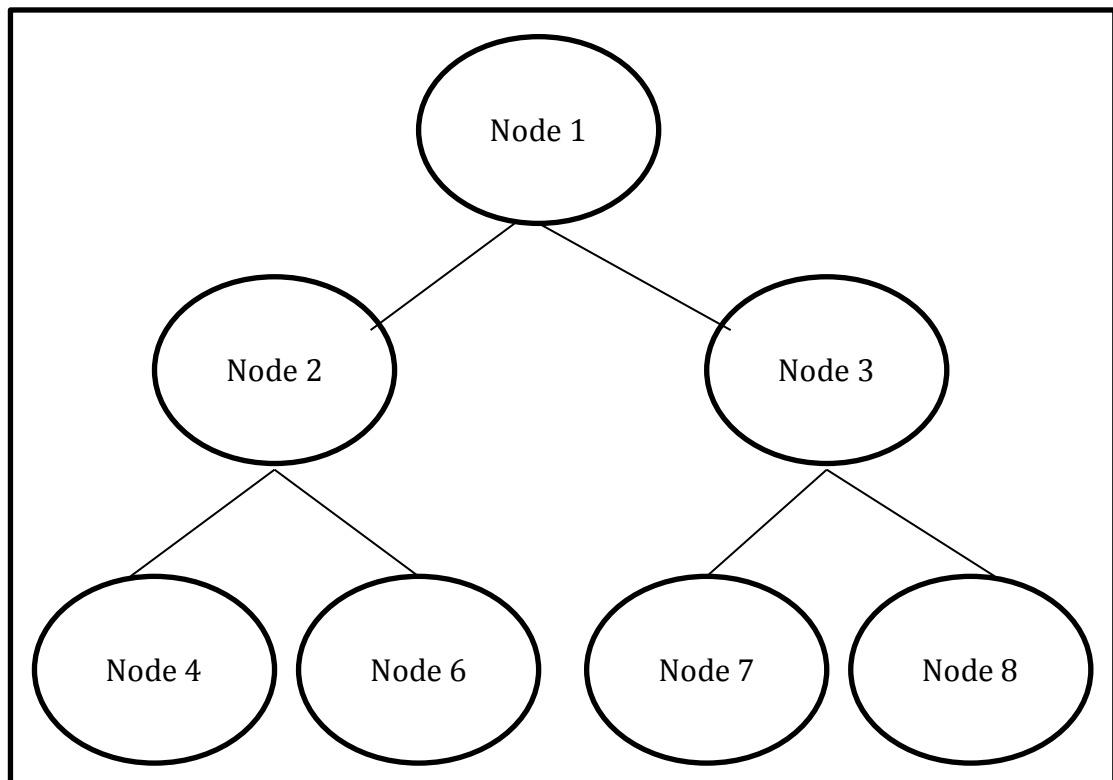


Figure 16 Tree Topology

Galton-Watson trees

Let  $\mu$  be a critical or subcritical offspring distribution. This means that

$\mu$  is a probability measure on  $Z_+$  such that

$$\sum_{k=0}^{\infty} k\mu(k) \leq 1$$

It's a trivial case where  $\mu(1) = 1$ . There is a unique probability

distribution  $Q_\mu$  on  $T$  such that

$$(i) \quad Q_\mu(k_\phi = j) = \mu(j), j \in Z_+$$

(ii) For every  $j \geq 1$  with  $\mu(j) > 0$ , the shifted trees  $\theta_1 T, \dots, \theta_j T$  are independent under the conditional probability  $Q_\mu(\cdot | k_\phi = j)$  and their conditional distribution is  $Q_\mu$ .

A random tree with distribution  $Q_\mu$  is called a Galton-Watson tree with offspring distribution  $\mu$ , or in short a  $\mu$ -Galton-Watson tree. Let  $T_1, T_2, \dots$  be a sequence of independent  $\mu$ -Galton-Watson trees. We can associate with this sequence a height process obtained by concatenating the height functions of each of the trees  $T_1, T_2, \dots$ . More precisely, for every  $k \geq 1$ , set

$$H_n = H_{n - (\#(T_1) + \dots + \#(T_{k-1}))} (T_k) \quad \text{if} \quad \#(T_1) + \dots + \#(T_{k-1}) \leq n < \#(T_1) + \dots + \#(T_k)$$

The process  $(H_n, n \geq 0)$  codes the sequence of trees. Although the height process is not a Markov process, except in very particular cases, it turns out to be a simple functional of a Markov chain, which is even a random

walk.

Let  $T_1, T_2, \dots$  be a sequence of independent  $\mu$ -Galton-Watson trees, and let  $(H_n, n \geq 0)$  be the associated height process. There exists a random walk  $V$  on  $\mathbb{Z}$  with initial value  $V_0 = 0$  and jump distribution  $v(k) = \mu(k + 1)$ , for  $k = -1, 0, 1, 2, \dots$ , such that for every  $n \geq 0$ ,

$$H_n = \text{Card} \left\{ k \in \{0, 1, \dots, n-1\} : V_k = \inf_{k \leq j \leq n} V_j \right\}$$

By definition,  $H_n$  is the generation of the individual visited/communicated at time  $n$ , for a particle that visits the different vertices of the sequence of trees one tree after another and in lexicographical order for each tree. Write  $R_n$  for the quantity equal to the number of younger brothers (younger means greater in the lexicographical order) of the individual visited at time  $n$  plus the number of younger brothers of his father, plus the number of younger brothers of his grandfather etc. Then the random walk that appears in the lemma may be defined by

$$V_n = R_n - (j-1) \quad \text{if } \#(T_1) + \dots + \#(T_{j-1}) \leq n < \#(T_1) + \dots + \#(T_j)$$

$V$  is a random walk with jump distribution  $v$ . The role of the random walk  $V$  in this formula is played by a Lévy process  $X = (X_t, t \geq 0)$  without negative jumps. the process  $X$  started at the origin will immediately hit both  $(0, \infty)$  and  $(-\infty, 0)$ . The law of  $X$  can be characterized by its Laplace functional  $\psi$ , which is the nonnegative function on  $\mathbb{R}^+$  defined by

$$E\left[\exp(-\lambda X_t)\right] = \exp(t\psi(\lambda))$$

By the Lévy-Khintchine formula and our special assumptions on  $X$ , the function  $\psi$  has to be of the form

$$\psi(\lambda) = \alpha\lambda + \beta\lambda^2 + \int \pi(dr) (e^{-\lambda r} - 1 + \lambda r)$$

where  $\alpha, \beta \geq 0$  and  $\pi$  is a  $\sigma$ -finite measure on  $(0, \infty)$  such that

$$\int \pi(dr) (r \wedge r^2) < \infty, \quad S_t = \sup_{s \leq t} X_s, \quad I_t = \inf_{s \leq t} X_s$$

Define  $H_t$  as the “measure” of the set  $\left\{s \leq t : X_s = \inf_{s \leq r \leq t} X_r\right\}$ . The process

$(H_t, t \geq 0)$  is called the  $\psi$ -height process, or simply the height process. In



the same way as the discrete height process codes the genealogy of a sequence of independent Galton-Watson trees, the continuous height process represents the genealogical structure of continuous-state branching processes, which are the continuous analogues of Galton-Watson processes.

Local times play an important role in the sequel, in particular in the applications to spatial branching processes. The local time of  $H$  at level  $a \geq 0$  and at time  $t$  is denoted by  $L_t^a$  and these local times can be defined through the approximation

$$\lim_{\varepsilon \rightarrow 0} E \left[ \sup_{s \leq t} \left| \varepsilon^{-1} \int_0^s 1_{\{\alpha < H_r < \alpha + \varepsilon\}} dr - L_s^a \right| \right] = 0$$

Since  $H$  is in general not Markovian nor a semimartingale, one cannot use the standard methods of construction of local time. The Ray-Knight theorem for the height process states that if  $T_r = \inf \{t \geq 0 : X_t = -r\}$ , for  $r > 0$ , the process  $(L_{T_r}^a, a \geq 0)$  is a continuous-state branching process with branching mechanism  $\psi$  (in short a  $\psi$ -CSBP) started at  $r$ . The Ray-Knight theorem corresponds to the intuitive fact that the population at generation  $a$  is a branching process. Continuous-state branching

processes are the only possible scaling limits of discrete-time Galton-Watson branching processes. The excursion of the  $\psi$ -height process codes a continuous branching structure.

Consider a spatial open set  $D$  with  $x \in D$ , to get a full description of the reduced spatial tree, one only needs to compute the joint distribution of the path  $W_0^D = W_{\tau_D}(\cdot \wedge m_D)$  that is the common part to all paths that do exit  $D$ , and the number  $N_D$  of branches at the first branching point. Conditionally on the pair

### *Mesh Topology Network*

In this topology is a point to point connection to other nodes or instruction. It allows for continuous connections and reconfiguration around broken and blocked paths by hopping from node to node until reached to destination.

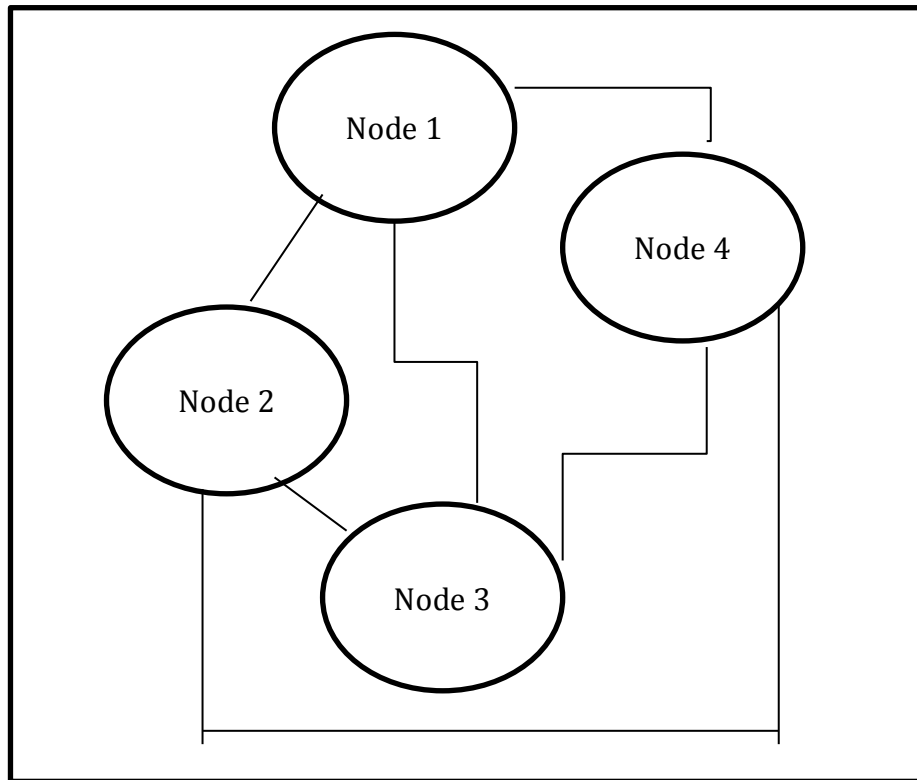


Figure 17 Full Mesh

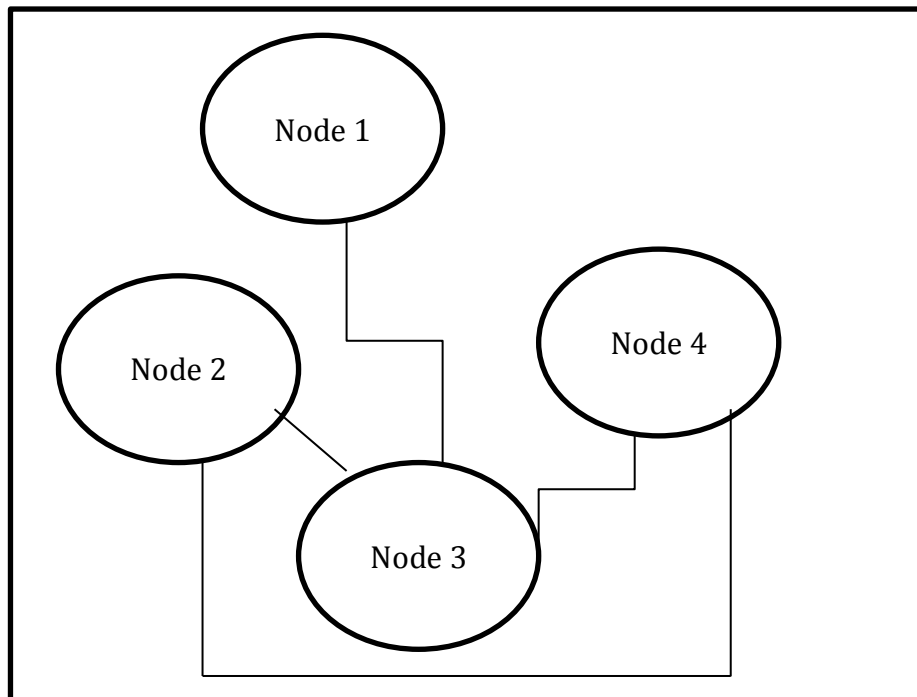


Figure 18 Partial Mesh

| Parameters | BUS  | STAR | RING | TREE | MESH |
|------------|------|------|------|------|------|
| Flexible   | yes  | yes  | no   | yes  | no   |
| Extension  | easy | easy | easy | easy | poor |
| Robust     | no   | yes  | no   | no   | yes  |

Table 7 A Comparison of Simple Network Topologies

*Random network (random graph)*

Random graphs were first presented by P. Erdos and E. Reyni.(1959).

They defined random graph as N nodes connected with n edges which

are chosen randomly from  $\frac{N(N-1)}{2}$  possible edges. In total there are

precisely  $C_{\frac{N(N-1)}{2}}^n$  different graphs with N nodes and n edges possible,

from which any graph is equiprobable.

An alternative definition is the binomial model: We start with N nodes and connect each pair of the nodes with probability p. Consequently the total number of edges is a random variable with the expectation value

$E(n) = p \frac{N(N-1)}{2}$ . If  $G_0$  is a graph with  $N$  nodes and  $n$  edges, the

probability of obtaining it by this graph construction process is binomial

$$P(G_0) = p^n (1-p)^{\frac{N(N-1)}{2} - n}$$

The construction of a graph is often called the evolution process.

Starting with a set of  $N$  isolated vertices, the graph develops by the successive addition of random edges. The graphs obtained at different stages of this process correspond to larger and larger connection probabilities  $p$ , eventually obtaining a fully connected graph

$$p \rightarrow 1 \Rightarrow n = N \left( \frac{N-1}{2} \right).$$

In a random graph with connection probability  $p$  the degree  $k_i$  of a node  $i$  follows a binomial distribution with parameters  $p$  and  $N-1$  :

$$P(k_i = k) = C_{N-1}^k p^k (1-p)^{N-1-k}$$

This probability represents the number of ways in which  $k$  edges can be drawn from a certain node: the probability of  $k$  edges is  $p^k$ , the probability of the absence of additional edges is  $(1-p)^{N-1-k}$ , and there

are  $C_{N-1}^k$  equivalent ways of selecting  $k$  endpoints to these edges. If  $i$  and  $j$  are different nodes  $P(k_i=k)$  in  $P(k_j=k)$  are close to be independent random variables.

Expected number of nodes with degree  $k$  is:

$$E(X_k) = NP(k_i=k) = NC_{N-1}^k p^k (1-p)^{N-1-k} = \lambda_k$$

The diameter of a graph is the maximal distance between any pair of its nodes. The diameter of a disconnected graph, which is made up of several isolated chunks, is infinite. Sometimes diameter is defined as the largest diameter of graph's components, but there are cases in which this definition can be misleading.

Random graphs tend to have small diameters if connection probability  $p$  is not too small. This is due to the fact that random graph is likely to be spreading: with a large probability the number of nodes at distance  $l$  from a given node is not much smaller than  $\langle k \rangle^l$  - in this case the graph would need to be a tree. Equating  $\langle k \rangle^l$  with  $N$ , diameter is proportional

with  $\frac{\ln(N)}{\ln(\langle k \rangle)}$ , thus it depends logarithmically on the number of nodes.

Diameter of random graphs has been studied by many authors. A general conclusion is that for most values of the connection probability  $p$ , almost all graphs have precisely the same diameter. This means when we consider all graphs with  $N$  nodes and connection probability  $p$ , the range in which the diameter values vary is very small, concentrated around:

$$d = \frac{\ln(N)}{\ln(pN)} = \frac{\ln(N)}{\ln(\langle k \rangle)}$$

If  $\langle k \rangle = pN < 1$ : Graph is composed of isolated trees. Diameter of a graph equals the largest diameter of its subtrees.

If  $\langle k \rangle = pN > 1$ : A giant cluster appears. The diameter of a graph equals the diameter of a giant cluster.

If  $\langle k \rangle = pN \geq \ln(N)$ : the graph is fully connected. Its diameter is concentrated on a few values around  $\frac{\ln(N)}{\ln(\langle k \rangle)}$ .

Complex networks exhibit a large degree of clustering. If we consider a node in a random graph and its first neighbours, the probability that two of these neighbours are connected is equal with the probability that two randomly selected nodes are connected. Consequently the clustering coefficient of a random graph is

$$C_{G(N,p)} = p = \frac{\langle k \rangle}{N}$$

### *Scale free network*

Many large networks are scale free: their degree distribution follows a power law for large  $k$ . Even for those real networks for which  $P(k)$  has an exponential tail, the degree distribution significantly deviates from a Poisson. Random graph theory and the WS model are unable to reproduce this feature.

A shift from modelling network topology to modelling the network assembly and evolution is required to get insight into mechanisms responsible to create scale – free networks. While the goal of the other models (random graphs and small - world models) is to construct a graph



with correct topological features, modelling scale free networks puts the emphasis on capturing the network dynamics. The assumption behind evolving or dynamic networks is that if we capture correctly the processes that assembled the networks that we see today, then we will obtain their topology correctly as well. Dynamics takes the driving role, topology being only a by product of this modelling philosophy.

Random networks and small worlds assume that we start with a fixed number  $N$  of nodes that are then randomly connected or rewired, without modifying  $N$ , the actual number of nodes. In contrast, most real world networks describe open systems, which grow by the continuous addition of new nodes. Starting from a small number of nodes, the number of nodes increases through the lifetime of the network by the subsequent addition of new nodes.

Most real networks exhibit preferential attachment, such that the likelihood of connecting to a node depends on the node's degree. (For example, a webpage will more likely include hyperlinks to popular documents with already high degree, because such highly connected documents are easy to find, etc). These two ingredients, growth and preferential attachment, inspired the introduction of the scale free (SF) model that has a power law degree distribution. The algorithm of the SF

model is the following:

1. Growth: Starting with a small number  $(m_0)$  of nodes, at every timestep we add a new node with  $m \leq m_0$  edges that link the new node to m different nodes already present in the system.

1. Preferential attachment: When choosing the nodes to which the new node connects, we assume that the probability  $\Pi$  that a new node will be connected to node  $i$  depends on the degree  $k_i$  of node  $i$ , such that

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j}$$

After  $t$  timesteps this algorithm results in a network with  $n = t + m_0$  nodes and  $mt$  edges. Numerical simulations indicated that this network evolves into a scale free state with the probability that a node has  $k$  edges following a power law with an exponent  $\gamma_{SF} = 3$ , where the scaling exponent is independent of  $m$ , the only parameter in the model. The average path length is smaller in the SF network than in a random graph for any  $N$ , indicating that the heterogeneous scale - free topology is more efficient in bringing the nodes close than the homogeneous

topology of random graphs.

The average path length calculated from generalised scale-free forced graphs estimation

$$l \approx \left( \frac{\ln \left[ \frac{N}{z_1} \right]}{\ln \left[ \frac{z_2}{z_1} \right]} \right) + 1$$

where  $z_1$  and  $z_2$  is the number of first and second neighbours. While this fit is good for a random graph it underestimates the average path length of the SF network, as it does with the real networks.

#### 2.2.2.2.2 DEFINING VARIABLES

A crucial feature of EWOM is that marketers are capable of monitoring the process of EWOM. Hence, marketers can obtain large database containing recorded detailed EWOM participant's behaviors (Bonfrer and Dreze, 2009), such as when they tweet and when the tweet gets retweeted. It is not straightforward to observe the process of EWOM volume development. Therefore, it is important to retain only certain variables that are relevant to the EWOM volume development process.

Figure 19 summarizes a three-stage process that an EWOM participant may go through during a twitter EWOM volume development process. In the first stage, an individual/company posts a seeding tweet (original tweet) on twitter at time  $t_1$  as source  $s$ . At the end of this stage, the participant decides with probability  $\phi_{12}^s$  to go to the second stage of the process and retweets the seeding tweet as a viral tweet (retweet) at time  $t_2$ . If the participant does not read or ignore the seeding tweet, the probability to exit the EWOM volume development process is  $1 - \phi_{12}^s$ . As the seeding tweet gets retweeted as a viral tweet by a twitter user, a viral tweet become present and it is stage one from another individual/participant's perspective. Finally, an participant's tweet gets retweeted by  $x$  twitter users.

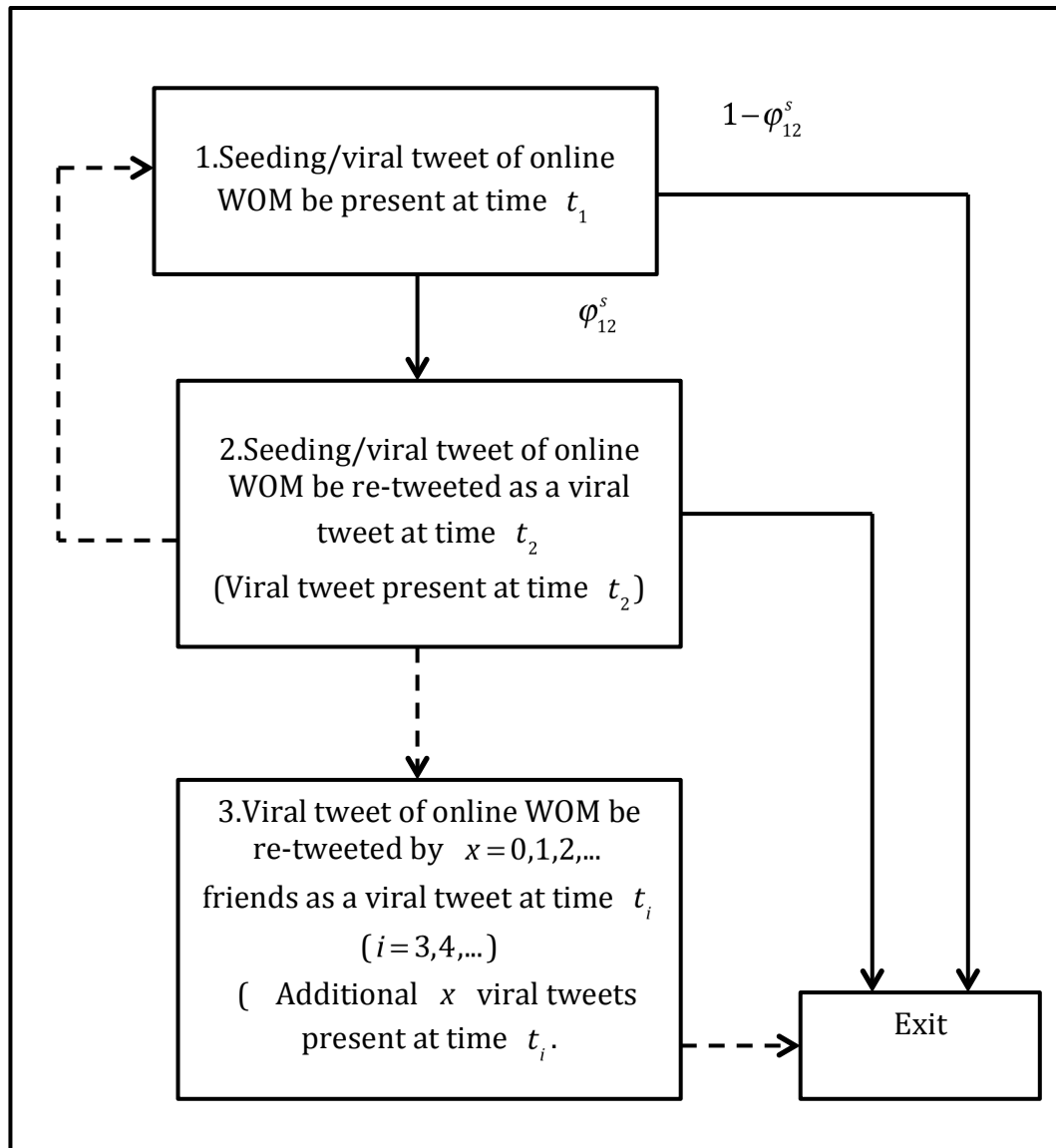


Figure 19 An EWOM Volume Development Process from a Participant's Perspective (Twitter)

The same process applies to Chinese version of twitter- Weibo (Figure 20).

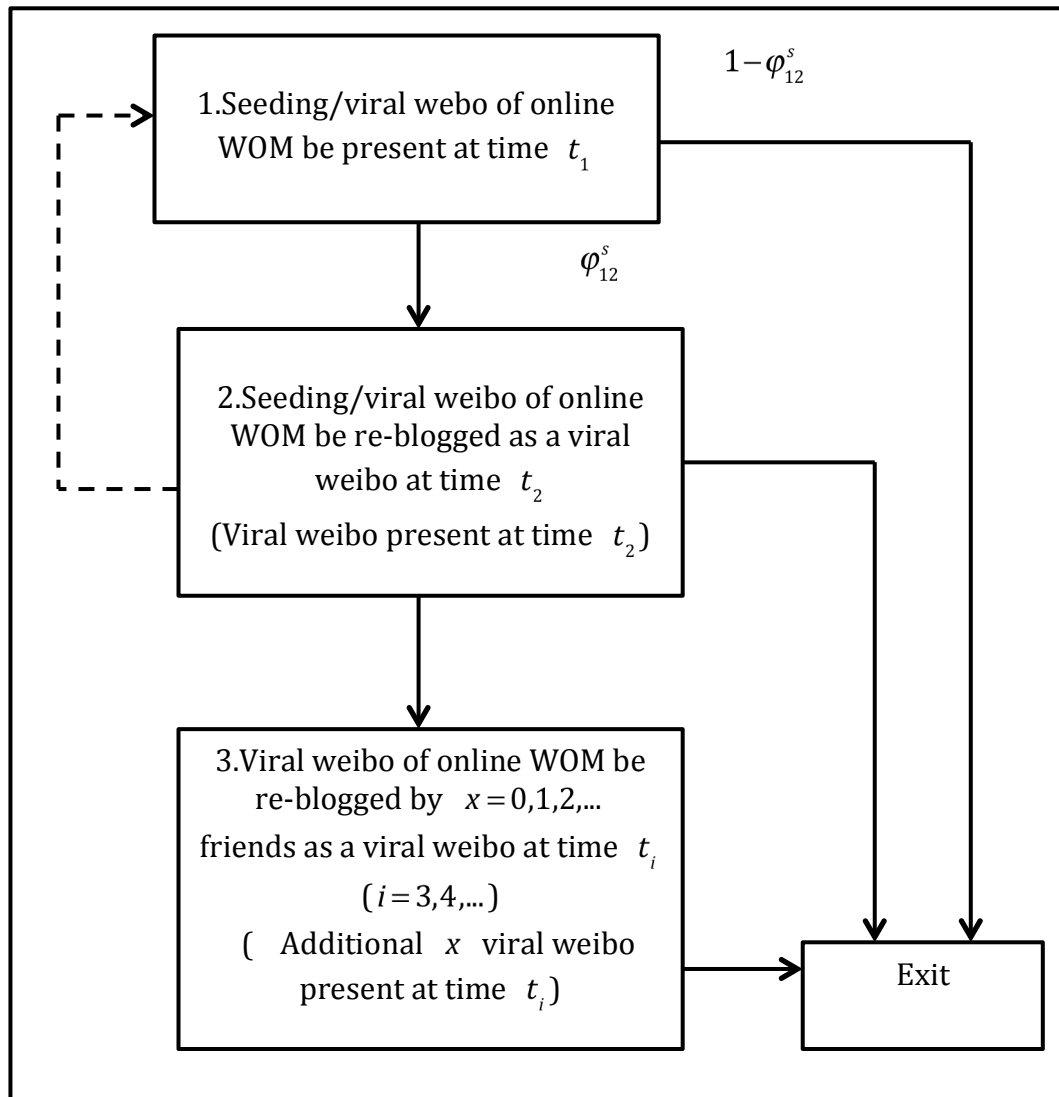


Figure 20 An EWOM Volume Development Process from a participant's Perspective (Weibo)

Figure 19 and Figure 20 show that the number of social networking site users who read the post is not necessarily the same as the number of social website users who ultimately participate in the EWOM volume development process, as the number depends on the probability  $\varphi_{12}^s$ .

To manage EWOM volume development process on social networking sites such as twitter and weibo, marketers need to obtain data through monitoring the stages illustrated in Figure 19 and 20 for each individual participant. Specifically, marketers need to register the following variables:

- (1) The source of the viral tweet/weibo (i.e. seeding tweet/weibo),
- (2) If and when a participant arrives at each stage
- (3) How many retweets a participant activates

This leads to a dynamic database in which each row represents a participant and in this database, corresponding variables get updated when a participant switches to the next stage. New rows are added each time a new participant occur. Such database can be automatically generated in real time during the process of EWOM volume development or be automatically generated according to historical data obtained from the Internet.

Before developing the mathematical WOM volume development model in the methodology section, Table 8 below listed the notations for the modeling of WOM volume.

Table 8 Variables of the WOM Volume Model

|                       |   |
|-----------------------|---|
| $t \in [0, \dots, T]$ | Denote continuous time, with $t=0$ as the start and $t=T$ the end of the EWOM volume development process  |
| $Y(t)$                | Denote the cumulative number of EWOM volume on a social website in the EWOM volume development process at time $t$  |
| $U(t)$                | Denote the number of social network site users who did not retweet / reblog the SEEDING tweet/weibo yet after the seeding post be presented on that user's social networking site page. |
| $W(t)$                | Denote the number of social network site users who did not retweet / reblog the VIRAL tweet/weibo yet after the viral post be presented on that user's social networking site page.     |
| $G(t)$                | Denote the vector $[U(t), W(t), Y(t)]$  |
| $s$                   | Denote all the retweeting and reblogging sources.<br>i.e. $s \in \{\text{seeding posts, viral posts}\}$   |
| $\beta$               | Denote the average number of retweets/reblogs a participant gets.   |



|               |  |
|---------------|--|
| $\phi_{12}^s$ | Denote the probability of retweeting/reblogging upon seeing the tweet/weibo posted by source $s$ |
| $1/\gamma_u$  | Denote the average time between a seeding post be posted and be retweeted/reblogged              |
| $1/\gamma_w$  | Denote the average time between a viral post be posted and be retweeted/reblogged                |

### 2.2.3 THE OUTCOME OF WOM VOLUME

Most of the current research on the outcome of WOM volume examines the economic effects of online WOM volume. The measurement of WOM volume is commonly the number of online user reviews, and high WOM volume has been shown to significantly improve marketing campaign outcome (Bao, and Chang, 2014).

Recent studies also identify a more intricate relationship between WOM volume and retail sales, which can be summarized by a positive feedback mechanism (Godes, and Mayzlin, 2004). In addition to its influence on sales, WOM volume is also an outcome of retail sales. A larger volume of online WOM (high WOM volume) increases the consumer awareness of the product or service, which leads to a higher

possibility of purchase. In addition to this role as a sales-influencer, the volume of WOM is meanwhile a sales outcome. The higher past sales imply a larger number of reviewers, which leads to more user-generated WOM (higher WOM volume). An empirical study (Duan, Gu, and Whinston, 2008) further explicitly supported this assertion that movie revenues have a positive influence on the volume of online WOM, which in turn has an influence on box office performance. The volume of WOM depends on the number of reviewers, which can be inferred by retail sales, so it is endogenous in nature (Zhou and Duan, 2015). This corresponds to the discussions in section 2.1.5.3 The Network Coproduction Model And Complex Network Topology Model. Furthermore, research reported a positive relationship between WOM volume and market share (Uncles et al. 2010). It is also found that as an extrinsic, high-scope cue (Purohit and Srivastava 2001), high-volume WOM is more diagnostic than is low-volume WOM for consumer decision-making (Khare et al. 2010).

In summary, WOM volume has been shown to significantly improve market outcome (Bao and Chang, 2014; Liu, 2006). The larger volume of user reviews can better attract consumers' attention to the product and accordingly result in a higher sales result (Godes and Mayzlin. 2004).

## 2.3 THE CAUSE, DEVELOPMENT AND OUTCOME OF WOM MARKETING: WITH PARTICULAR REFERENCE TO THE MODELING OF WOM VALENCE

### 2.3.1 OVERVIEW OF PREVIOUS LITERATURE REGARDING THE CAUSE OF WORD-OF-MOUTH VALENCE

#### *1. Satisfaction*

The dominant model for conceptualizing and measuring customer satisfaction has been the expectancy disconfirmation theory. This view holds that customers evaluate a product or service performance and compare their evaluation with their expectations prior to purchase or consumption (Oliver 1980). In this approach to satisfaction as a post-choice evaluative judgment regarding a specific purchase selection, satisfaction is understood by its transaction specific component (Oliver 1981). Another approach sees satisfaction as the customers' evaluations of multiple experiences with the same product or service provider over time (Bolton and Drew 1991), and given that this cumulative construct incorporates previous experiences, the cumulative satisfaction construct will contain an element of customer attitude (Westbrook and Oliver

1991). Subsequent studies, however, have demonstrated that, in addition to the cognitive view, customer satisfaction also contains emotional components (Liljander and Strandvik 1997; Oliver and Westbrook 1993; Straus and Neuhaus 1997). A recent study (Martin et al. 2008) agrees with Zeelenberg and Pieters (2004) in suggesting that emotionally based satisfaction is a stronger predictor of future behavioral intentions than traditional cognitive measures.

There are a number of studies supporting the significant effect of satisfaction on WOM and eWOM (Brown et al. 2005; Heckman and Guskey 1998; Heitmann et al. 2007; Hennig Thureau et al. 2002; Mittal et al. 1999; Price and Arnould 1999; Söderlund 2006; Swan and Oliver 1989; Wangenheim and Bayón 2014). The level of customer satisfaction has an influence on two purchase behaviors, namely, repurchase intentions and WOM (Bearden and Teel 1983; Maxham and Netemeyer 2002a, b; Oliver 1980; Ranaweera and Prabhu 2003; Richins 1983). Specifically, the likelihood of customers spreading WOM will depend on their satisfaction level for at least two reasons. First, the extent to which the product or service performance exceeds the customer's expectations might motivate him or her to tell others about his or her positive experience. In the context of service recovery, for instance, the salience and recency of the experience might explain why satisfaction

with the recovery prompts customers to tell family and friends about their positive experience (Maxham and Netemeyer 2002b). Second, to the extent that the customer's expectations are not fulfilled, possibly creating a customer regret experience, this customer will engage in WOM behavior as a form of "venting" his or her negative emotions, such as anger and frustration, reducing anxiety, warning others, and/or seeking retaliation (Anderson 1998; Oliver 1997; Richins 1984; Sweeney et al. 2005). Indeed, there are a number of studies supporting the significant effect of satisfaction on WOM (Brown et al. 2005; Heckman and Guskey 1998; Heitmann et al. 2007; Hennig-Thurau et al. 2002; Mittal et al. 1999; Price and Arnould 1999; Söderlund 2006; Swan and Oliver 1989; Wangenheim and Bayón 2007).

Wilson et al. (2012) found that posting on consumer opinion sites is more positively correlated with wanting to warn others about a bad experience than expressing satisfaction. Additionally, consumers who had bad experiences might be ego-defensive (Daugherty et al., 2008) and seek to "take vengeance" (Yoo and Gretzel, 2008).

## 2. *Loyalty*

Loyalty is defined in the marketing context as “an intention to perform a diverse set of behaviors that signal a motivation to maintain a relationship with the focal firm, including allocating a higher share of the category wallet to the specific service provider, engaging in positive word of mouth (WOM), and repeat purchasing” (Sirdeshmukh et al. 2002, p.20). Note that this conceptualization considers positive WOM as a component of loyalty. This approach is common in a great number of studies in the marketing literature (Bloemer et al. 1999; Jones and Sasser 1995; Jones and Taylor 2007; Lam et al. 2004; Zeithaml et al. 1996), and we found that it was employed in 40 studies reviewed in our meta-analysis. These studies could not, however, be included because they did not present specific results for the WOM construct. Moreover, in a disloyalty situation, in which customers switch providers, they are also likely to spread negative WOM about the provider in order to reduce their cognitive dissonance (Wangenheim 2005).

Early views of loyalty focused on repeat purchase behavior. For example, Brown (1952) classified loyalty into four categories, (a) undivided loyalty, (b) divided loyalty, (c) unstable loyalty, and (d) no loyalty, as

revealed by the purchase patterns of consumers. Lipstein (1959) and Kuehn (1962) measured loyalty by the probability of product repurchase. Some researchers (Day, 1969; Jacoby & Chestnut, 1978) have suggested that these behavioral-based definitions are not sufficient because they do not distinguish between true loyalty and spurious loyalty, due to factors such as lack of consumer choice. For example, a consumer may appear to be loyal to a particular store or brand but, in reality, may have no other choice because he or she lacks convenient transportation to travel to another store and the preferred brand is not carried by the nearby store.

Jacoby (1971) expressed the view that loyalty is a biased behavioral purchase process that results from a psychological process. Other researchers have defined loyalty as “a favorable attitude toward a brand resulting in consistent purchase of the brand over time” (Assael, 1992; Keller, 1993). Keller suggested that loyalty is present when favorable attitudes for the brand are manifested in repeat buying behavior. Gremler (1995) suggested that both attitudinal and behavioral dimensions needed to be incorporated in measuring loyalty.

According to Matos and Rossi (2008), loyalty is an antecedent of WOM valence. Because to the extent customers are more loyal to a given

provider, they are also more likely to (1) give positive recommendations of the company to the individuals in their reference group (friends and relatives), (2) have greater motivation for processing new information about the company, and (3) have stronger resistance to being persuaded by contrary information (Dick and Basu 1994, p. 107). Moreover, in a disloyalty situation, in which customers switch providers, they are also likely to spread negative WOM about the provider in order to reduce their cognitive dissonance (Wangenheim 2005). In other words, they try to convince themselves about their decision by convincing others, which is one of the strategies often used for reducing post-decision dissonance. As mentioned before, customers might also engage in negative WOM for other reasons such as to release negative emotions, to warn others, and/or to retaliate (Richins 1984; Sweeney et al. 2005).

Relationship managers are interested in the loyalty intentions of customers who have been successfully attracted to the firm's offering (Bhattacharya, 1998; Sheth and Parvatiyar, 1995). Gruen, Osmonbekov and Czaplewski (2005) consider positive eWOM as expressed in customers' willingness to recommend the product to others online, as the Internet has emerged as a source and an outlet for electronic word-of-mouth (eWOM) communication for customers (Hennig-Thurau et al., 2004). Gruen et al.(2006) has examined loyalty intentions to



include the repurchase of the firm's offering and WOM as an outcome (Richins, 1983) of the C2C know-how exchange in their research. The rationale for their proposed direct effect of know-how exchange on loyalty intentions is supported by the norm of reciprocity (von Hippel, 1988), where obligations among parties in the know-how exchange are formed to reciprocate value received. These obligations suggest that there is a cost to leaving the organization, which includes the loss of important relationships built through informal know-how trading (Cohen, 1992). Burnham et al. (2003) classify such costs as a specific type of switching cost termed "personal relationship loss costs". Customers engaged in C2C knowhow exchange may develop affective bonds with other customers, which encourage them to produce WOM valence.

Moreover, customers who are more satisfied and more pleased with the seller are more likely to become loyal spreaders of positive WOM on behalf of and favouring the seller (Lovelock and Wirtz, 2007). And when customers perceive higher satisfaction on the quality of service they have received from their purchase, they become more willing to provide positive WOM on behalf of the seller (Athanasopoulos, Gounaris, & Stathakopoulos, 2001).

### *3. Quality*

Empirical studies have demonstrated that service quality is a relevant predictor of WOM valence (Bloemer et al. 1999; Boulding et al. 1993; Harrison-Walker 2013; Zeithaml et al. 1996). Harrison-Walker (2001) argued that the effect of service quality on WOM praise is contingent on industries.

Customers' perceptions of service quality have an important relationship with their behavioral responses, especially loyalty and WOM. For WOM, when evaluations of service quality are high, the customer's behavioural intentions in terms of recommendations are favourable (positive WOM), strengthening the relationship between customers and the company (Parasuraman et al. 1988; Zeithaml et al. 1996). On the other hand, when customers perceive service performance as inferior, they are likely to manifest complaining behavior, including private responses (negative WOM) and/or defection (Zeithaml et al. 1996). Hence, customers recommend the company to others when they perceive high service quality and spread negative WOM when they perceive low service quality.

Empirical studies have demonstrated that service quality is a relevant predictor of WOM valence (Bloemer et al. 1999; Boulding et al. 1993; Harrison-Walker 2001; Zeithaml et al. 1996). A positive relationship presented in these studies demonstrates that the higher (lower) the perceived quality, the higher (lower) the WOM valence of the customers.

Service quality is conceptualized as “an attitude that is defined by an individual’s importance-weighted evaluation of the performance of the specific dimensions of a service” (Cronin and Taylor, 1992). Many studies have investigated customers’ perceptions of service quality as a predictor of customers’ behavior intentions, such as WOM valence. Boulding et al. (1993) indicated that service quality positively affects behavioral outcomes such as loyalty and positive WOM valence. Zeithaml et al. (1996) proposed a model of the behavioral consequences of service quality and suggested that perceived service quality was related to positive behavioral intentions including WOM valence, purchase intentions, complaining behavior, and price sensitivity. Based on Zeithaml et al.’s study, Alexandris et al. (2002) investigated the degree to which behavioral intentions could be explained by the dimensions of service quality. Harrison-Walker (2001) also investigated service quality as an antecedent of WOM valence and support the level

of perceived service quality positively affecting the favorableness of an individual's WOM valence giving.

#### *4. Commitment*

Commitment can be defined as “an enduring desire to maintain a valued relationship” (Moorman et al. 1992, p. 316). This definition is in agreement with Dwyer et al. (1987) conceptualization of buyer-seller relationships and is also consistent with Morgan and Hunt's (1994, p. 23) definition of commitment as “an exchange partner believing that an ongoing relationship with another is so important as to warrant maximum efforts at maintaining it.” Commitment is measured in the marketing literature either as a multidimensional construct (Gruen, Summers, and Acito, 2000) or a unidimensional construct (Morgan and Hunt 1994). In the multidimensional approach, commitment is composed of “affective” (positive emotional attachment), “continuance” (perceived costs associated with leaving the organization), and “normative” (perceived moral obligation toward the organization) commitment. Some authors consider two dimensions, namely “affective” and “high sacrifice (calculative) commitment” (Fullerton 2003; Harrison-Walker 2001; Jones et al. 2007). While the former is related to

the customer identification with, and involvement in, a particular organization, the latter refers to the customer's sense of being "locked in" to the service provider, due to constraints like loss of benefits and costs for switching provider. On the other hand, the unidimensional approach measures commitment as an overall evaluation of the customers' engagement with the organization.

Brown et al. (2005) have demonstrated in their longitudinal study that for higher-commitment customers, positive WOM behavior is less dependent on the satisfaction level. The reason is that high-commitment customers talk positively about the company regardless of their satisfaction level, whereas low-commitment customers will provide favorable recommendations to the extent that they are satisfied. This finding is in agreement with other studies which establish that commitment has a positive relationship with WOM (Hennig-Thurau et al. 2002; Lacey et al. 2007).

Customer commitment leads the customer to positive eWOM communication, such as raised intention to make referrals (Liljander and Strandvik, 1995). Customers with higher intention to make commitments are more likely to tell people about positive aspects of an organisation (Bettencourt, 1997). Making positive referrals for a company is one of

the ways that a customer shows his behaviour loyalty to an organisation. Bettencourt (1997) shows how customer satisfaction, via the mediating effect of customer commitment, affects customer loyalty. When customer commitment is the mediator, the higher the customer commitment, and the more likely it is for the customers to take the initiative and make referrals about satisfactory experiences with the organisation. And this is accentuated in the case of more satisfied customers (Kuan, Yang, and Cheng, 2005). Singh and Sirdeshmukh (2000) indicate that customer trust is a key variable between pre-purchase and post-purchase that can bring out long-term loyalty from the customer and lead the customer to form a tighter future relationship with the seller. After the customer has accumulated more trust in the seller, the customer's commitment can help him foster more post consumption interactions with the seller (Morgan & Hunt, 1994). HarrisonWalker (2001) suggests that customer trust can truly reflect the emotional attachment that the customer has to the seller during or after the purchase.

### *5. Trust*

Trust refers to “a willingness to rely on an exchange partner in whom one has confidence” (Moorman et al. 1993, p. 82). For Morgan and Hunt (1994, p. 23), trust exists “when one party has confidence in an exchange partner’s reliability and integrity.” Thus, confidence and reliability are two important factors for conceptualizing trust in the marketing context. Research in this field has demonstrated that customers’ trust - either in the overall organization or in the employees—is significantly influenced by customers’ satisfaction (Kau and Loh 2006; Morgan and Hunt 1994; Ranaweera and Prabhu 2003; Singh and Sirdeshmukh 2000). These findings show that the higher (lower) the customer’s satisfaction with the organization, the higher (lower) his or her trust in it.

Trust also has an important effect on behavioral constructs, especially on the customer’s propensity to leave or stay with the same service provider (Garbarino and Johnson 1999; Morgan and Hunt 1994; Singh and Sirdeshmukh 2000). Indeed, empirical findings have shown that higher levels of trust are associated with a greater tendency to offer favourable WOM – positive WOM valence (Garbarino and Johnson 1999; Gremler

et al. 2001; Ranaweera and Prabhu 2003). This is based on the rationale that customers mostly provide recommendations to other individuals of their reference group, such as a friend or a relative, and, thus, a customer will be more likely to endorse a provider that he or she has previous experience with and confidence in (Gremler, Gwinner, and Brown 2001).

Another possible reason for the influence of trust on WOM is an indirect effect through satisfaction. Trust creates benefits for customers such as lower anxiety, uncertainty, and vulnerability about the transaction. These benefits influence satisfaction, which in turn affects WOM, especially in a service context that is relatively more complex (Garbarino and Johnson 1999; Hennig-Thurau et al. 2002).

The customer's trust in relational sales contexts is definable as a customers' confident belief that she may rely on the salesperson to behave in such a manner that serves the long-term interest of the customer (Crosby et al., 1990). Westbrook (1981) confirms that customer satisfaction is his emotional appraisal of the series of interactions he has had with the seller; it positively correlates to his trust in the seller. According to Singh and Sirdeshmukh, (2000) a customer's satisfaction after purchase directly influences his post-purchase evaluations (WOM valence) of competence trust. When there is trust



between the seller and the buyer, the parties value this relationship, and they continue to make commitments to this relationship to sustain it over the long haul (Morgan and Hunt, 1994). Duhan and Sandvik (2009) point out that the higher the degree of confidence an advertiser has in the ad agency, the more the advertiser is willing to make efforts to maintain their long-term relationship

Trust and satisfaction are equally important drivers of eWOM valence as consumers offer emotionally strong commentary on the people who provided them with goods or services (Ranaweera & Prabhu, 2003). Related research also found that trust raised the willingness of the purchaser to make repeated purchases and to make referrals, and it also found that trust lowered the desire of the consumer to spread negative eWOM (Goles, Lee, Rao, and Warren, 2009). According to Tsao and Hsieh (2012) customer trust can exert their positive influence on positive eWOM valence through the mediating effect of customer commitment.

## 6. *Perceived value*

Zeithaml (1988) defines value as “the consumer’s overall assessment of the utility of a product based on perceptions of what is received and what is given.” or in other words, a trade-off between benefits or gets (quality, convenience, volume, etc.) and costs or gives (money, time, efforts, etc.).

The importance of perceived value in electronic commerce stems from the fact that it is easy to compare product features as well as prices online. According to Bakos (1991), the search costs in electronic marketplaces are lower, resulting in more competitive prices to the consumer. According to Parasuraman and Grewal (2000), perceived value is a function of “a ‘get’ component—i.e., the benefits a buyer derives from a seller’s offering—and a ‘give’ component—i.e., the buyer’s monetary and nonmonetary costs in acquiring the offering.”

A number of researchers have concluded that a significant number of electronic commerce customers are motivated by low prices (Goldberg, 1998; McCune, 1999; Tanaka, 1999). Researchers have also established a positive relationship between perceived value and intention to

purchase/repurchase (Dodds, Monroe, and Grewal, 1991; Parasuraman and Grewal, 2000).

Previous studies have investigated the influence of service quality on customers' behavioral intentions (Boulding et al. 1993; Zeithaml 1988). Based on this literature, Hartline and Jones (1996) proposed that perceived value also has an influence on customers' behavioral intentions, especially on WOM valence. One explanation is that customers who perceive that they receive relatively high value tend to become more committed to the organization and seek to recommend others of the reference group to become loyal to the same organization (McKee et al. 2006). Also, perceived value might have an influence on WOM valence because it is a more tangible signal in the service encounter since it includes price in the "give" component, and price can be considered a more extrinsic and tangible attribute when compared to other cues used to infer service quality by customers, such as competence and responsiveness of employees (Hartline and Jones 1996). Consistent with the above rationale, perceived value has been hypothesized as a predictor or a correlate of WOM in a number of studies (Durvasula et al. 2004; Gruen et al. 2006; Hartline and Jones 1996; Keiningham et al. 2007; McKee et al. 2006).

Moreover, according to the meta-analysis of antecedents of WOM valence by Matos and Rossi (2008), Satisfaction, Loyalty, Quality, Commitment, Trust, and Perceived Value have significant effects on WOM valence, which are consistent with recent aforementioned studies on eWOM. Therefore, these elements are to be used in the modeling of WOM valence.

## 2.3.2 ARTIFICIAL NEURAL NETWORKS AND THE DEVELOPMENT OF WOM VALENCE

### 2.3.2.1 A REVIEW OF ARTIFICIAL NEURAL NETWORKS

A thorough study of ANNs requires knowledge of neurophysiology, cognitive science/psychology, physics (statistical mechanics), control theory, computer science, artificial intelligence, statistics/mathematics, pattern recognition, computer vision, parallel processing, and hardware (digital/analog/VLSI/optical). New developments in these disciplines continuously nourish the field. On the other hand, ANNs also provide an impetus to these disciplines in the form of new tools and representations. This symbiosis is necessary for the vitality of neural network research. Communications among these disciplines ought to be encouraged.

ANN research has experienced three periods of extensive activity. The first peak in the 1940s was due to McCulloch and Pitts' pioneering work. The second occurred in the 1960s with Rosenblatt's perceptron convergence theorem and Minsky and Papert's work showing the limitations of a simple perceptron. 6 Minsky and Papert's results dampened the enthusiasm of most researchers, especially those in the

computer science community. The resulting lull in neural network research lasted almost 20 years. Since the early 1980s, ANNs have received considerable renewed interest. The major developments behind this resurgence include Hopfield's energy approach<sup>7</sup> in 1982 and the back-propagation learning algorithm for multilayer perceptrons (multilayer feed- forward networks) first proposed by Werbos,<sup>8</sup> reinvented several times, and then popularized by Rumelhart et al. in 1986. Anderson and Rosenfeld provide a detailed historical account of ANN developments.

A technical neural network consists of simple processing units, the neurons, and directed, weighted connections between those neurons. Here, the strength of a connection (or the connecting weight) between two neurons  $i$  and  $j$  is referred to as  $w_{i,j}$

A *neuron* (or nerve cell) is a special biological cell that processes information

A neural network is a sorted triple  $(N, V, w)$  with two sets  $N$ ,  $V$  and a function  $w$ , where  $N$  is the set of neurons and  $V$  a set  $\{(i, j) | i, j \in N\}$

whose elements are called connections between neuron  $i$  and neuron  $j$ . The function  $w:V \rightarrow R$  defines the weights, where  $w((i,j))$ , the weight of the connection between neuron  $i$  and neuron  $j$ , is shortened to  $w_{i,j}$ . Depending on the point of view it is either undefined or 0 for connections that do not exist in the network.

Learning is a comprehensive term. A learning system changes itself in order to adapt to e.g. environmental changes. A neural network could learn from many things but, of course, there will always be the question of how to implement it. In principle, a neural network changes when its components are changing. Theoretically, a neural network could learn by:

1. developing new connections,
2. deleting existing connections,
3. changing connecting weights,
4. changing the threshold values of neurons,
5. varying one or more of the three neuron functions (remember: activation function, propagation function and output function),
6. developing new neurons, or
7. deleting existing neurons (and so, existing connections).

The change in weight is the most common procedure. Furthermore, deletion of connections can be realized by additionally taking care that a connection is no longer trained when it is set to 0. Moreover, a researcher can develop further connections by setting a non-existing connection (with the value 0 in the connection matrix) to a value different from 0. Thus, the neural network learn by modifying the connecting weights according to rules that can be formulated as algorithms. Therefore a learning procedure is always an algorithm that can easily be implemented by means of a programming language.

A training set (named  $P$ ) is a set of training patterns, which researchers use to train the neural net.

The most interesting characteristic of neural networks is their capability to familiarize with problems by means of training and, after sufficient training, to be able to solve unknown problems of the same class. This approach is referred to as generalization.



*ANN Models V.S. Structural Equation Models*

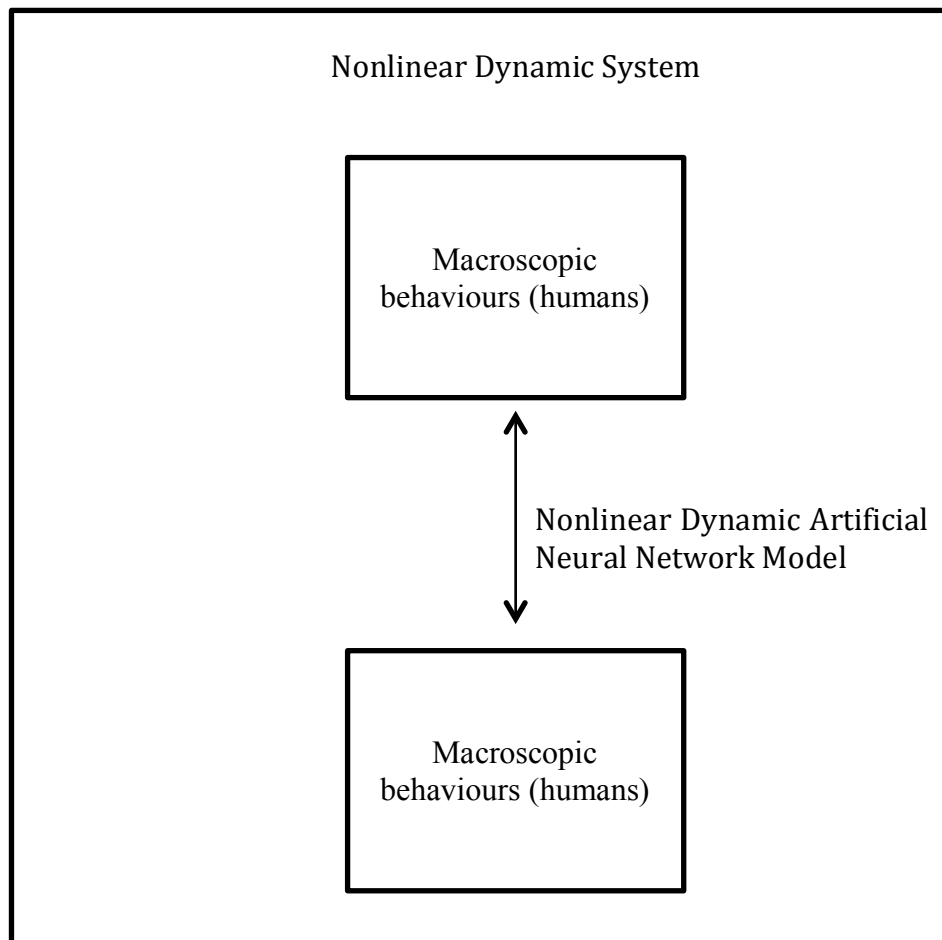


Figure 21 Nonlinear Dynamic ANN

Hair, Black, Babin, Anderson, and Tatham (2006) suggest that “in simple terms, SEM estimates a series of separate, but interdependent, multiple regression equations simultaneously by specifying the structural model used by the statistical program”.

Structural equation models (SEMs) were developed in the field of econometrics and first applied to imaging data by McIntosh and Gonzalez-Lima (MacIntosh and Gonzalez-Lima, 1991). They comprise a set of regions and a set of directed connections. Importantly, a causal semantics is ascribed to these connections where an arrow from A to B means that A causes B. Causal relationships are thus not inferred from the data but are assumed a priori (Pearl, 1998).

An SEM with particular connection strengths implies a particular set of instantaneous correlations among regions. One can therefore set the connection strengths so as to minimise the discrepancy between the observed and implied correlations and thereby fit a model to data. If, for example, one partitions a given fMRI data set into those scans obtained under two different levels of an experimental factor, then one can attribute differences in the estimated connection strengths to that factor, and so conclude that a pathway has been activated. To date, SEMs have been the most widely used model for connectivity analyses in neuroimaging (Goncalves and Hull, 2003).

Figure 19 illustrate the nonlinear dynamic nature of ANN models. Artificial intelligence (AI) has been established as the area of computer

science dedicated to production software capable of sophisticated, intelligent, computations similar to those that the human brain routinely performs. It includes methods, tools and systems devoted to simulate human methods of logical and inductive knowledge acquisition, reasoning of brain activity for solving problems. There are two main categories of AI developments. The first includes methods and systems that simulate human experience and draw conclusions from a set of rules, such as expert systems. The second includes systems that model the way the brain works. The ANN methodology is based on the attempt to model the way a biological brain processes data. It is thus quite different from standard statistical methods of analysis. ANN represents a promising modeling technique especially for data sets having the kind of non-linear relationships, which are frequently encountered in psychological process.

### 2.3.2.2 ANN SELECTION

In this section, three typical ANN models are discussed and compared so as to select an appropriate one for the modeling of WOM valence. They are McCulloch Pitts Neuron Model, ADALINE Neuron Model and Back Propagation Network Model.

#### *McCulloch Pitts Neuron Model*

The earliest neural network model is the McCulloch Pitts neuron model. In this model, all the neurons are connected by directed weighted paths. It is noted that the activation of a McCulloch Pitts neuron is binary which means that at any time step the neuron may fire or may not fire. The weights associated with the communication links may be excitatory where the weights are positive or may be inhibitory where the weights are negative. The threshold plays an important role in the McCulloch Pitts neuron. There is a fixed threshold for each neuron and if the net input to the neuron is greater than or equal to the threshold then the neuron fires. Let inputs be  $I_1, I_2, I_3, \dots, I_m$ , and output  $y$ . As aforementioned discussions, the linear threshold gate simply classifies the set of inputs into two different classes. Thus the output  $y$  is binary. Mathematically, such a function can be described using these equations:

$$Sum = \sum_{i=1}^N I_i W_i$$

$$y = f(\text{Sum})$$

$W_1, W_2, W_3, \dots, W_m$  are weight values normalized in the range of either  $(0,1)$  or  $(-1,1)$  and associated with each input line,  $\text{Sum}$  is the weighted sum, and  $T$  is a threshold constant. The function  $f$  is a linear step function at threshold  $T$  as shown in figure 20. The symbolic representation of the linear threshold gate is shown in figure 21.

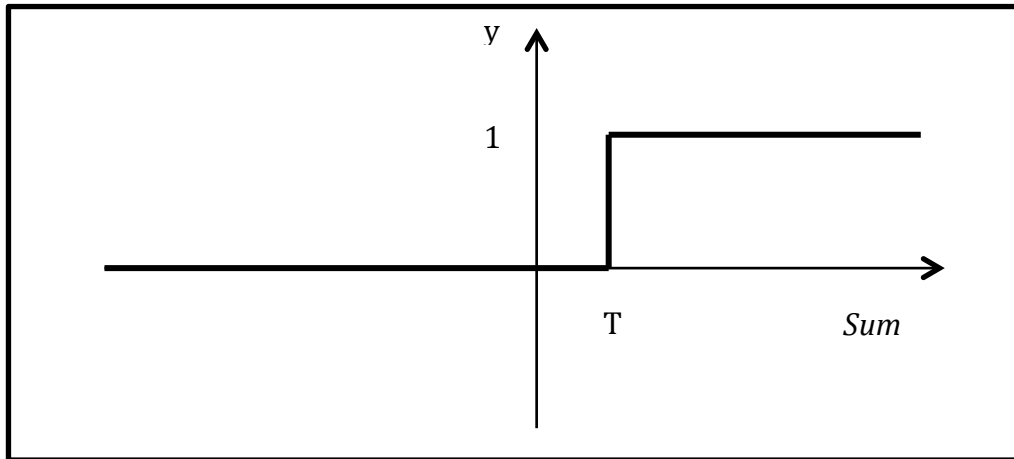


Figure 22 Linear Threshold Function

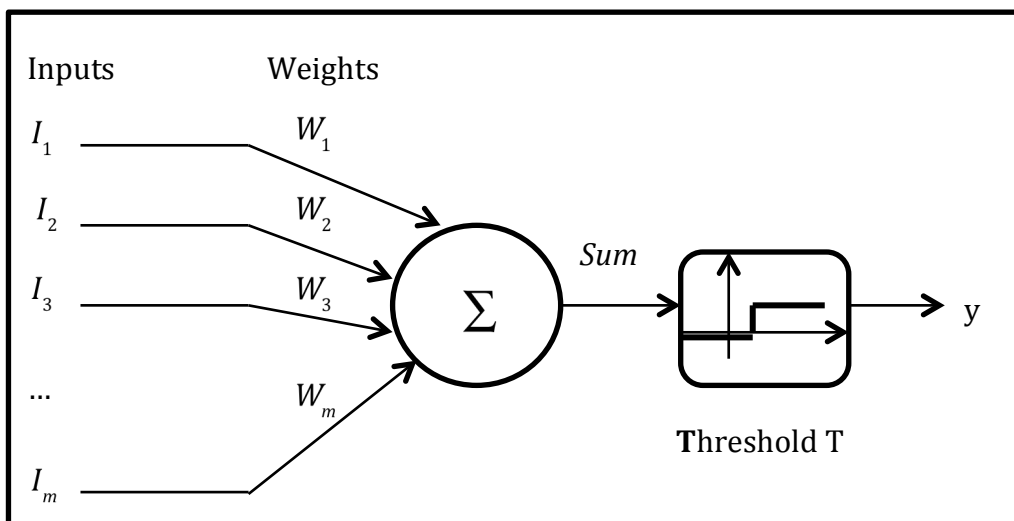


Figure 23 McCulloch Pitts Neuron Model

If hidden layer is absent, the weights for the connections from input layer to output layer and threshold are obtained as inputs. Activations for the training input units and target output units are set. The net inputs to the neuron present in the output layer are calculated. If a calculated net input is greater than or equal to threshold then the calculated output unit is set to 1; else if the calculated net input is less than the threshold then the calculated output unit is set to 0.

If all the calculated output units are equal to the target output units then it means that the simulation is done correctly based on the weights and threshold obtained as input and the response is considered as positive; else the response is considered as negative and weights and threshold are again obtained as inputs and the whole process is repeated again and again till time all the calculated output units are becoming equal to the target output units.

McCulloch Pitts neuron model could be applied in various simulation modelling occasions such as creating linear judgements. Nevertheless, this model is so simplistic that it only generates a binary output and also the weight and threshold values are fixed. For the EWOM valence development process, the binary output can not satisfy the complexity of

the valence model. Therefore, a more advanced ANN model should be adopted.

#### *ADALINE Neuron Model*

ADALINE neuron model is ADaptive LINEar neural network. The units with linear activation function are called linear units. A network with a single linear unit is called ADALINE or ADaptive LINEar neuron. In an ADALINE, the input – output relationship is linear. ADALINE uses bipolar activation for the input signals and their target output.

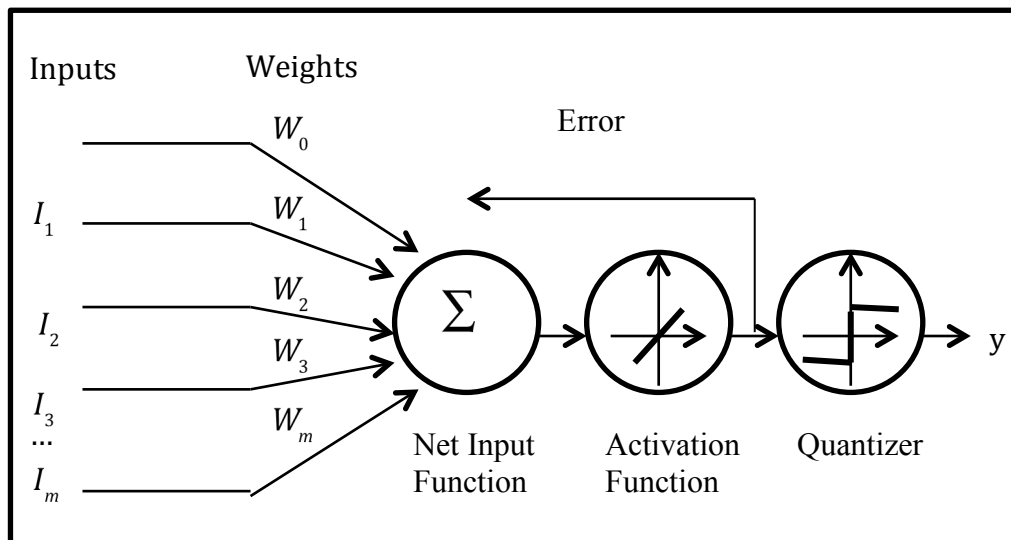


Figure 24 ADALINE Neuron Model

The weights between the input units and the output units are adjustable. The bias in ADALINE acts as an adjustable weight. The ADALINE

network is trained using the delta rule. The delta rule adjusts the weights to reduce the Least Mean Square error or LMS error which is the difference between the net input to the calculated output unit and the target output unit. Since the delta rule adjusts the weights to reduce the LMS error, the delta rule is also known as LMS rule.

In the training phase the weights and bias are initialised to some random values but not zero. The learning rate  $\alpha$  is set. Activations for the training input units and target output units are set. The net inputs to the output neurons are calculated. The differences between the net inputs to the calculated output units and the target output units are calculated. The squared differences between the net inputs to the calculated output units and the target output units are calculated and summed up to form total mean square error.

According to the delta rule, the weight vector units and bias vector are changed. The weight vector is found to change proportionately to the product of the input, learning rate and the difference between the net input to the output neuron and the learning signal. The bias vector is found to change proportionately to the product of the learning rate and the difference between the net input to the output neuron and the learning signal. Here the learning signal is equal to the neuron's target



output. The training is done until the total mean square error has reached to a smaller value than a specific tolerance value.

In the testing phase, the net inputs to the target output neurons are calculated taking weights from the training phase after setting the activations of the input units. If a calculated net input is greater than or equal to threshold, then the calculated output is set to 1; else if a calculated net input is less than threshold then the calculated output is set to -1. If all the calculated output units are equal to the target output units then the response of the network is considered as positive; else the response of the network is considered as negative.

For the modelling of WOM valence, ADALINE Neuron Model is more advanced and complicated than McCulloch Pitts Neuron Model. It can be applied as an adaptive filter to predict the next value of a stationary random process. However, as the discussion aforementioned, ADALINE Neuron Model can only solve linearly separable problems, which is not much applicable for the case of WOM valence modelling. Therefore, there is a need to find another type of ANN model for the modelling of WOM valence.

### *Back Propagation Network*

Back propagation network uses gradient-descent based delta learning rule, also known as back propagation rule thereby minimises the total squared error of the output computed by the network. It provides a computationally efficient method for changing the weights in the network with differentiable activation function units to learn a set of input output patterns. It aims to achieve the balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good responses to the input patterns that are similar.

Figure 23 illustrated the back propagation network.

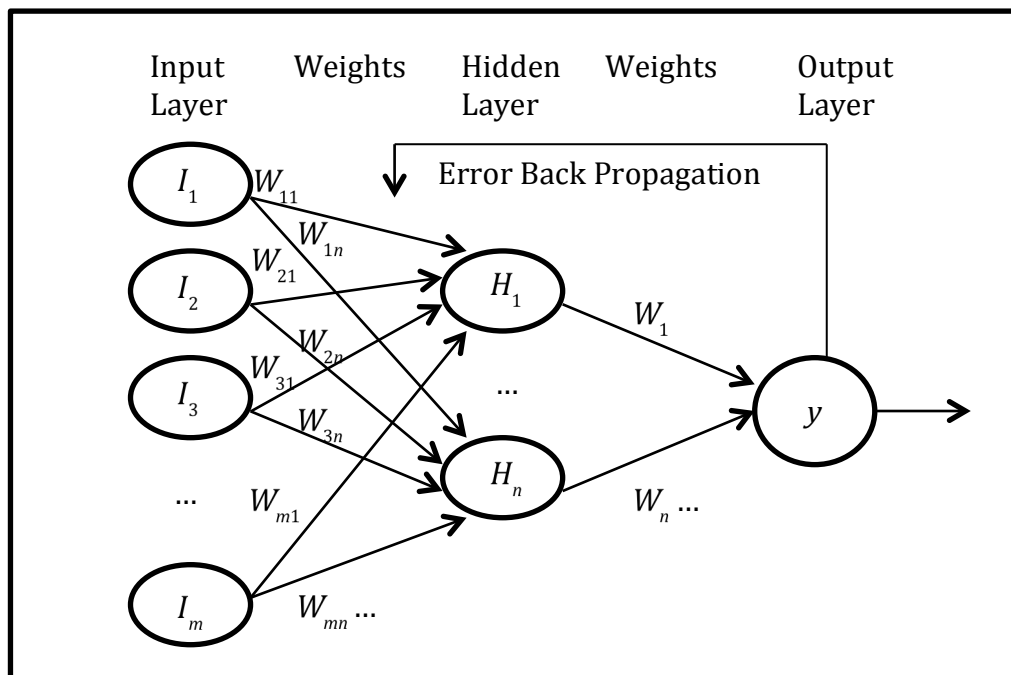


Figure 25 Back Propagation Neural Network Model

In the training phase, the weights, biases and the learning rate  $\alpha$  are initialised to small random values. Activations for the training input units and target output units are set. The net inputs to the neurons present in the hidden layer are calculated. The output of the hidden unit is calculated by applying the binary sigmoidal activation function. Activations for the hidden units are set. The net inputs to the neurons present in the output layer are calculated. The output of the output unit is calculated by applying the binary sigmoidal function. The error correction term due to the error at hidden units are computed based on which the changes in weights and biases are done to the input layer backwards. The network is trained till certain number of epochs reached or till the calculated output equals the target output.

In the testing phase, the net inputs to the hidden layer neurons are calculated taking weights from the training phase after setting the activations of the input units. The output of the hidden unit is calculated by applying the binary sigmoidal activation function. Activations for the hidden units are set. The net inputs to the neurons present in the output layer are calculated. The output of the output unit is calculated by applying the binary sigmoidal function. If all the calculated output units are equal to the target output units then the response is considered as positive; else the response is considered as negative.

The back propagation neural network model is more complicated than ADALINE neuron model. The nonlinear nature of the activation function used by the hidden neurons allows chaotic time series to be forecasted. It illustrates advantages that they can adapt to new scenarios, they are fault tolerant and can deal with noisy data. For the modeling of WOM valence, the back propagation neural network model is sufficient and efficient for forecasting valence in the context of online WOM. Therefore, back propagation neural network model will be applied for the modelling of WOM valence in this thesis.

#### 2.3.2.3 DEFINING VARIABLES

In summary, the inputs for the back propagation neural network model for the modelling of WOM valence are shown in table 9.

| Inputs | Meaning         |
|--------|-----------------|
| $I_1$  | Satisfaction    |
| $I_2$  | Loyalty         |
| $I_3$  | Quality         |
| $I_4$  | Commitment      |
| $I_5$  | Trust           |
| $I_6$  | Perceived Value |

Table 9 Input variables defined for the modeling of WOM valence

### 2.3.3 THE OUTCOME OF WOM VALENCE

Previous literature studies the effect of WOM on measures of company performance such as customer satisfaction, customer loyalty, and future sales. In these studies, WOM is an antecedent or independent variable. For example, Nam et al. (2010) studied the effect of WOM on customer acquisition, retention, and usage for a new video-on-demand service and found that about 20% of new activations were due to WOM. There are many studies that have examined the relationship between product reviews and future product sales. The findings are mixed. Several studies have empirically shown that positive reviews are associated with higher sales, whereas negative reviews tend to hurt sales of experiential products like books and movies (Chevalier and Mayzlin 2006). Several other studies did not find a statistically significant relationship (Duan et al. 2005, Liu 2006). In addition, several studies have found that buyers seem to find movies and books that have generated a lot of reviews more interesting, thus driving more sales than those that have not received many comments (Dellarocas et al. 2005, Duan et al. 2005, Liu 2006).

The primary focus of much of the extant offline WOM literature has been on understanding the effect of WOM on the WOM recipient

(Bansal and Voyer, 2000; Brown and Reingen, 1987; East et al., 2008; Söderlund and Rosengren, 2007; Wang, 2011). On the other hand, except for the notable work by Garnefeld, Helm, and Eggert (2011), the research on examining the impact of offline WOM on the sender itself is rare (but see Moore, 2012 in the e-WOM context and Garnefeld, Eggert, Helm, & Tax, 2013 in the amplified WOM context).

EWOM research efforts fell into either: 1) Market-level, identifying the product information process by viewing eWOM as accumulated customer opinion, and its relationship with other market level signals, or, 2) Individual-level, identifying the customer's decision-making process by viewing the eWOM as informational, focusing on how the information affects a customer's decision-making process.

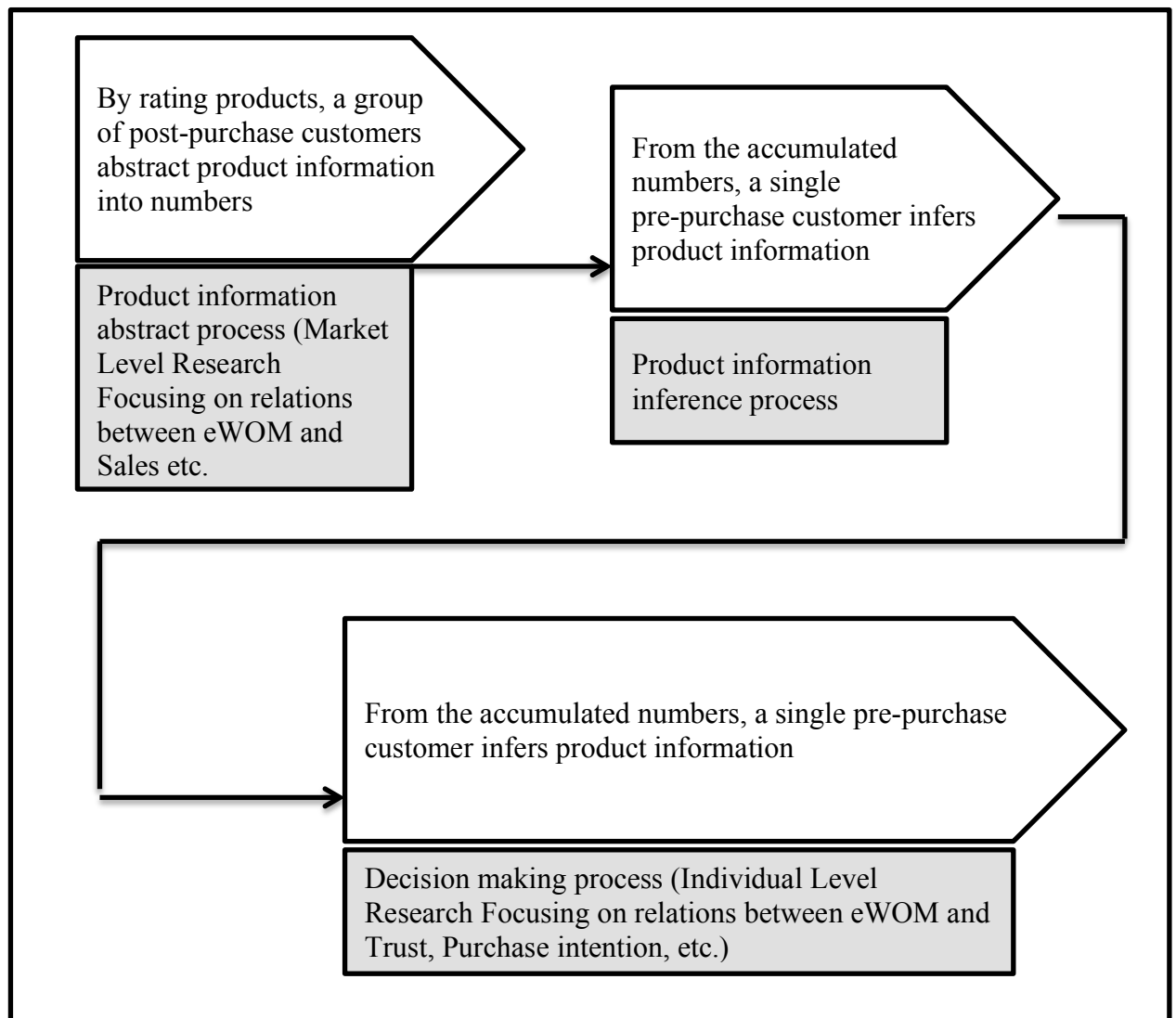


Figure 26 EWOM Activities (Lee and Lee , 2009)

Garnefeld et al. (2011) considered the impact of articulating positive WOM valence, Rahul and Francesca (2105) focused on the effect of articulating negative WOM valence on the sender.

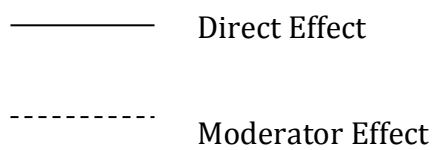
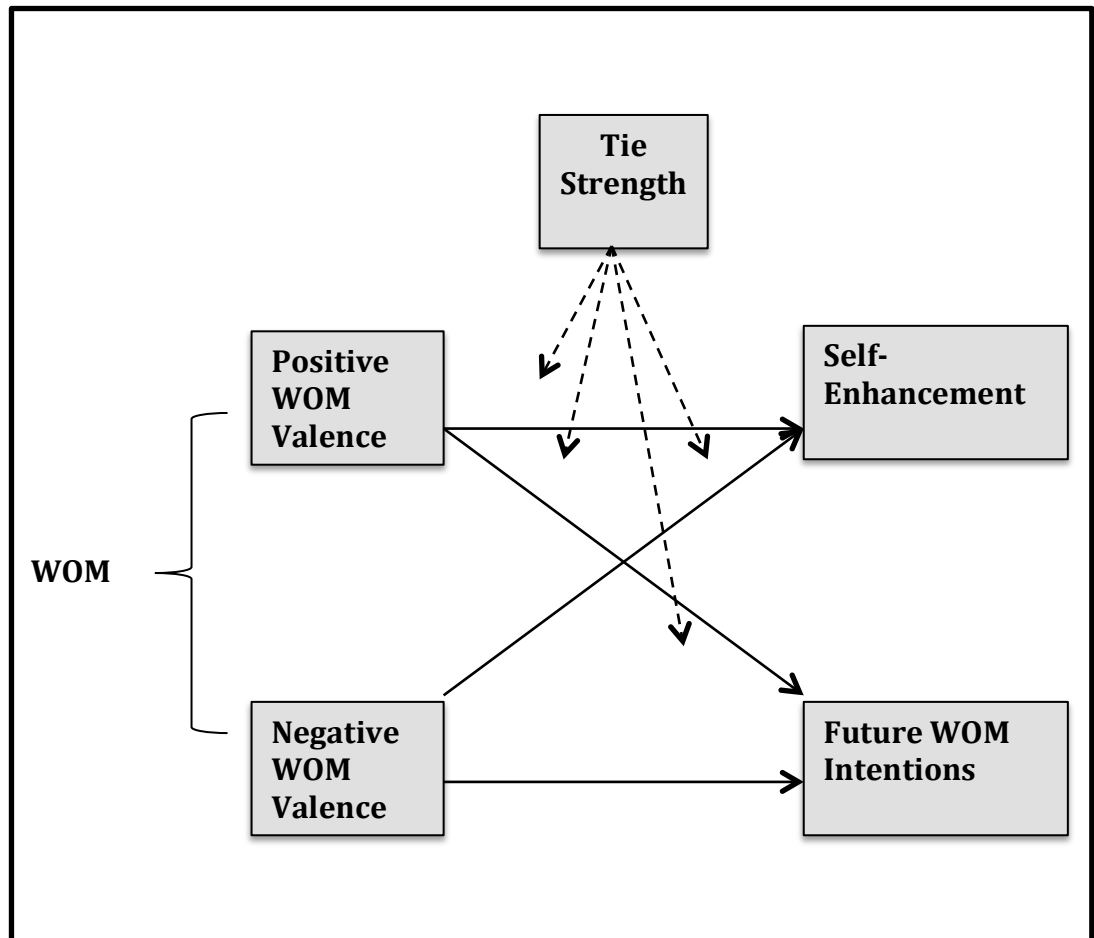


Figure 27 Effects of WOM valence (Chawdhary and Riley, 2015)

Angelis et al. (2012) found that senders are likely to transmit negative WOM about other people's negative brand experiences in order to



self-enhance. In the study of Chawdhary and Riley (2015), they postulate that a reverse effect also exists and that articulation of WOM is likely to influence the sender's own self-enhancement. Furthermore, they tested that this effect holds for both positive WOM and negative WOM. This is because an individual can project a good image amongst others by warning them about unsatisfactory service providers and thus potentially helping them avoid negative brand experiences.

Based on the research of Romaniuk (2012), the six possible outcomes of WOM-the conditions under which they may occur, and the research challenges/opportunities they presented are as follows.

|   |   |
|---|---|
| <p>PERSUASION<br/>(e.g. Li and Zhan, 2011; Filieri, and Mcleay, Fraser, 2014; Herr, Kardes, and John, 1991)</p> | <p>"Persuasion," in this instance, occurs when the WOM causes a large shift in brand-choice probabilities. This is the most commonly discussed outcome in marketing, when more than half of service consumers, according to one study, claimed to have found their new supplier via positive WOM (PWOM; Keaveney, 1995). It is important to consider the point that, for a large revision in probabilities to occur, the receiver must have room to move (East,</p> |
|---|---|

|  |  |
|--|--|
|  | <p>Hammond, and Lomax, 2008). For PWOM to have a positive persuasive shift, the initial chance of buying the brand needs to be low: if you begin with a zero or low probability of choosing a brand, WOM can turn an unlikely choice into a very likely choice.</p> <p>If, conversely, the brand was something you already were considering and predisposed to select, then any PWOM can only shift a "likely" choice into a "more likely" choice-movement that truly does not represent a persuasive effect. (In fact, it's more of a "Nudge")</p> <p>Similarly, with negative WOM (NWOM), a receiver needs to be highly likely to buy a product or service for a large drop to occur. If someone already is unlikely to buy a brand, hearing NWOM cannot have a persuasive effect. Given that most people are highly unlikely to buy most brands, NWOM will rarely affect someone who is in a position to be dissuaded.</p> <p>It also is important to note that just because WOM can persuade, that potential</p> |
|--|--|

|         |   |
|---------|---|
|         | <p>does not mean it will. Secondary factors also can have an impact on any WOM's effect. WOM that is expressed mildly-from someone with weak relationship ties or where the giver's expertise or taste is doubted-will have lower impact. Although WOM most often is discussed as a powerful force, in practice-even with the right pre-conditions- that power only sometimes is exerted.</p>   |
| NUDGING | <p>Nudging occurs when the WOM has a small effect on receivers-for instance, such as moving them from a 4-of-10-chance of buying a brand to 5-of-10. More consumers have the potential to be nudged, as nudging does not need a consumer predisposed to be highly likely or highly unlikely to buy the brand. Although the effect on any individual consumer may be small, it is an effect that can occur across a large number of consumers. And such mass, therefore, can make it a substantive force for the brand. Even more interesting is the notion that nudging also could include a "mere awareness" effect from neutral WOM. Given that up to 50 percent of</p> |

|  |   |
|--|---|
|  | <p>WOM is neutral (i.e., not explicitly positive or negative), the net effect of this nudging also could be quite substantive. The net effect of WOM's nudging consumers, therefore, might be greater than that of WOM's persuading people about brands.</p>  |
| <p>NO EFFECT<br/>(e.g. Yang et al., 2012; Yoo et al., 2013))</p> | <p>Not all WOM shifts the probability of the receiver's choosing a brand. Indeed, sometimes the receiver remains unmoved, and WOM is of no value to the brand. If a consumer is certain he or she is going to buy a particular product or service and gets positive advice about that brand, the WOM has no impact. Similarly, if someone is certain she or he will not buy a brand and hears something negative about it, that WOM also has no impact.</p> |
| <p>CONTRARIAN<br/>(e.g. Romaniuk , 2012)</p>                     | <p>It often is assumed that PWOM will have a positive effect and that NWOM will have a negative effect. There are instances, however, when the effect is contrary to expectations. PWOM can have a negative effect when a receiver distrusts the advice from a giver. For example, when a respondent in a recent</p>  |

|  |  |
|--|--|
|  | <p>study was asked why the PWOM she received actually reduced her likelihood of watching a television show, she commented, "It was my mum who recommended it, and I don't like watching what she watches." Similarly, NWOM can have a positive effect when it stimulates controversy. Hearing negative comments about a brand might make someone more curious-and so more inclined to act to satisfy this curiosity. Not considering that the effect direction can be contrary to expectations may introduce an error when attempting to quantify the impact of WOM.</p> |
| <p>PASSING ON<br/>(e.g. Strutton, ,<br/>Taylor, and<br/>Thompson, 2011;<br/>Lee et al., 2014))</p> | <p>Sometimes hearing WOM can stimulate more WOM. In these instances, the behavior of interest is not the receiver acting toward the brand but the receiver acting as an agent to <i>pass on</i> the WOM to someone else, who then may act on the WOM. Your WOM might have no effect on me, but I still might pass it on if I think it useful to someone else. Therefore, just concentrating on how your WOM influences me underestimates its impact.</p>   |

|   |   |
|---|---|
| <p>REINFORCEMENT<br/>FOR THE GIVER<br/>(e.g. McMahan<br/>, 1991; Krigolson et<br/>al., , 2009))</p> | <p>Attitudes are influential only if they are remembered. Even for fast-moving consumer goods, a considerable amount of time, for most people, elapses between purchases. The act of talking about the brand does make the brand more salient to the giver. This reinforcement can enhance the giver's likelihood of buying the brand, even if the receiver does nothing.</p> |
|---|---|

Table 10 Effects of WOM

## 2.4 VARIABLES FOR THE MODELING OF WOM VOLUME AND WOM VALENCE

In this section, the variables for the modeling of WOM volume and WOM valence were displayed. Moreover, the status WOM campaigns trying to achieve was discussed.

### 2.4.1 VARIABLES IN THE MATHEMATICAL EXPRESSIONS OF WOM VOLUME

|                       |   |
|-----------------------|---|
| $t \in [0, \dots, T]$ | Denote continuous time, with $t=0$ as the start and $t=T$ the end of the EWOM volume development process  |
| $Y(t)$                | Denote the cumulative number of EWOM volume on a social website in the EWOM volume development process at time $t$  |
| $U(t)$                | Denote the number of social network site users who t retweet / reblog the SEEDING tweet/weibo after the seeding post be presented on that user's social networking site page. |
| $W(t)$                | Denote the number of social network site users who retweet / reblog the VIRAL tweet/weibo after the viral   |

|               |  |
|---------------|--|
|               | post be presented on that user's social networking site page.  |
| $G(t)$        | Denote the vector $[U(t), W(t), Y(t)]$   |
| $s$           | Denote all the retweeting and reblogging sources.<br>i.e. $s \in \{seeding \text{ posts}, viral \text{ posts}\}$ |
| $\beta$       | Denote the average number of retweets/reblogs a participant gets.  |
| $\phi_{12}^s$ | Denote the probability of retweeting/reblogging upon seeing the tweet/weibo posted by source $s$                 |
| $1/\gamma_u$  | Denote the average time between a seeding post be posted and be retweeted/reblogged                              |
| $1/\gamma_w$  | Denote the average time between a viral post be posted and be retweeted/reblogged                                |

Table 11 Variables for the Modeling of WOM Volume



#### 2.4.2 VARIABLES FOR THE MODELING OF WOM VALENCE

| Inputs | Meaning         |
|--------|-----------------|
| $I_1$  | Satisfaction    |
| $I_2$  | Loyalty         |
| $I_3$  | Quality         |
| $I_4$  | Commitment      |
| $I_5$  | Trust           |
| $I_6$  | Perceived Value |

Table 12 Variables for the Modeling Of WOM Valence

#### 2.4.3 SUCCESSFUL VIRAL MARKETING CAMPAIGNS: HIGH WOM VOLUME AND POSITIVE WOM VALENCE

The two most important WOM attributes studied in the literature are volume (i.e., the amount of WOM information; e.g., Anderson 1998; Bowman and Narayandas 2001) and valence (i.e., whether the opinions from WOM are positive or negative; e.g., Herr, Kardes, and Kim 1991). Previous research has indicated that WOM valence can influence product sales by changing consumer valuation of the products (e.g., Chevalier and Mayzlin 2006; Mizerski 1982), and WOM volume plays an informative role by increasing the degree of consumer awareness and the number of informed consumers in the market (Liu, 2006).

### *High versus low WOM volume*

Previous studies have suggested that the volume of WOM can predict the sales of products and have demonstrated this both theoretically (McFadden and Train, 1996) and empirically for various product categories including TV shows (Godes and Mayzlin, 2004) and motion pictures (Duan et al., 2008; Liu, 2006). The reasoning behind WOM volume being a powerful predictor of product sales is that WOM volume increases the awareness about a product among consumers and leads to higher sales, and is also known as informative effect of WOM. Petty and Cacioppo (1984) show that individuals less involved in a decision are persuaded more when the number of arguments is greater, irrespective of argument quality, whereas involved decision makers can be persuaded by more arguments, but only if those arguments are strong. Consumers, through knowledge of other consumer's experiences concerning a particular product, can reduce the uncertainty associated with the product (Banerjee, 1992; Bikhchandani et al., 1992; Chen et al., 2004). . In other words, consumers build higher credibility on the products with higher WOM volume, which increases consumers' willingness to buy (Grewal et al., 1994; Harmon and Coney, 1982), especially for experience goods when the quality is uncertain

The volume of online WOM reflects the degree of consumer's interest. Online reviews have become a major information source for consumers. For example, book's sales rate correlates with its average review score on online stores such as amazon.com (Chevalier & Mayzlin, 2006). In response to the influence of online WOM, many studies have focused on aspects of online WOM, such as the source of information (Dichter, 1966; Myers & Robertson, 1972), the information's audience (Granovetter, 1983), the content shared (Phelps et al., 2004) and the process of online WOM diffusion (Godes & Mayzlin, 2004; Liu, 2006).

*Positive versus negative WOM valence*

It is intuitive that the valence of WOM influences consumer choices since consumers tend to rely on what other consumers have done before in order to decrease the uncertainty associated with the decision making process (Banerjee, 1992). If a consumer keeps on receiving consistent positive WOM during the service encounter, he/she will display a stronger tendency to purchase the service (Mazzarol et al., 2007).

As stated, WOM can be either positive or negative; what marketers are interested in is to promote positive WOM and to avoid negative WOM, since positive WOM is suggested to be the ultimate product success factor (Day, 1971). Thus the issue of how to promote positive WOM has

attracted large research attention (e.g. Murray, 1991; Harrison-Walker, 2001). Satisfied consumers may or may not result in positive WOM about the service; while a dissatisfied consumer has a strong tendency to tell others about his/her anger and even exaggerates the bad experience (Sjodin, 2007). However, there are only a few studies examining negative WOM. For example, Sjodin (2007) finds that negative WOM can cause current customers to criticize a brand extension and highlights the importance of dissatisfaction as a potential antecedent.

Godes and Mayzlin (2004) found that the effect of WOM valence via the average star rating in online bookstores showed mixed results depending on the bookstores. They found a significant WOM valence effect on sales for Amazon.com, but no effect for bn.com. Chevalier and Mayzlin (2006) use book reviews posted by customers at Amazon.com and Barnesandnoble.com online stores as a proxy for WOM. They find that though most reviews were positive, an improvement in a book's reviews led to an increase in relative sales at the site, and the impact of a negative review was greater than the impact of a positive one. In contrast, Liu (2006) shows that both negative and positive WOM increase performance (box office revenue) and found that the volume of WOM helps explain aggregate and weekly box office revenue, but the valence had no significant explanatory power, in his exploration of the temporal

relationship between user WOM and box office revenue. On the other hand, Duan et al. (2008) suggested that both a movie's box office revenue and WOM valence significantly influenced WOM volume and, in turn, WOM volume leads to higher box office performance. Yang et al (2012) found the significant effect for WOM valence only in the case of niche movies.

There is consensus in the literature that negative eWOM is an influential behavioral determinant (Brown et al., 2007; Sun, Youn, Wu, & Kuntaraporn, 2006). Due to the spread and adoption of new consumer-empowering technologies such as social media and mobile devices complaints and dissatisfied experiences can be communicated and distributed instantly within a huge network of other consumers (Van Noort & Willemsen, 2012). The majority of consumers puts trust into these disclosures when engaging in online buying behavior (Ye, Law, Gu, & Chen, 2012). A recent study indicates that in particular negative eWOM may have very strong effects on consumer behavior and even drives companies to make use of web care teams. These teams aim to service dissatisfied customers as a way to reduce the chance that negative opinions spread through and are adopted by the consumer population at large (Van Noort & Willemsen, 2012). Basically, consumers distribute negative eWOM to communicate a dissatisfying

consumption experience (Anderson, 1998). This unfavorable experience often is due to a malfunctioning product or an unfavorable customer service. The problems consumers experience can be enduring and occur for many different consumers at the same time or can be the result of infrequent lapses of product quality and service practices (Richins, 1984). Consumers share these experiences with others for a number of reasons. First, consumers may use negative WOM for themselves, for example to draw attention to the cause of their dissatisfaction in order to get a solution (Thøgersen, Juhl, & Poulsen, 2009) or as a mechanism to vent negative feelings in order to reduce anxiety (Nyer, 1997; Richins, 1984). Second, consumers may disclose unfavorable experiences to prevent others from enduring similar bad experiences (Litvin, Goldsmith, & Pana, 2008; Parra-López, Bulchand-Gidumal, Gutiérrez-Tano, & Díaz-Armas, 2011). The latter reason often is observed in situations where an individual participates in online communities, where social relationships with others are developed through sharing and discussing interest in products or services. Especially when consumers have received helpful support and advice themselves, this can motivate them to provide others with helpful advice as well (Brown, Broderick, & Lee, 2007). Third and finally, consumers may ventilate their thoughts and feelings on a bad experience openly as a way to encourage the company to improve its practices. In particular in situations where a relationship

exists, consumers may complain to assure that the issue is structurally solved (Zaugg & Jäggi, 2006). In relationships of high quality and trust such complaining behavior may be communicated openly (Forrester & Maute, 2001) via, for example online forums (Harrison-Walker, 2001). From a complaint management perspective, companies may even encourage such open complaining as it proves their commitment towards the customer and transparency of their operations (Hart, Heskett, & Sasser, 1990; Spreng, Harrell, & Mackoy, 1995).

According to the accessibility-diagnostics model (Feldman and Lynch 1988), whether consumers will use any accessible information for their decision-making depends on the diagnosticity of the information. A piece of product information is diagnostic if it helps consumers assign the product to a unique category and nondiagnostic if it has multiple interpretations or causes (Hoch and Deighton 1989).

Negative WOM information is more diagnostic, and researchers have found it to have a greater impact on consumers' adoption decisions than positive WOM information (e.g., Mizerski 1982).

Therefore, researchers and marketers are seeking to achieve high WOM

volume and positive WOM valence for successful viral marketing campaigns. The author of this study thus came up with Figure 28 to illustrate the goal of WOM performance.

|   |   |
|---|---|
| High WOM Volume<br>Negative WOM Valence | High WOM Volume<br>Positive WOM Valence |
| Low WOM Volume<br>Negative WOM Valence  | Low WOM Volume<br>Positive WOM Valence  |

Figure 28 High WOM Volume and Positive WOM Valence

This thesis will develop models that help to achieve high WOM volume and positive WOM valence in WOM campaigns as the highlighted area in Figure 6 and avoid other results indicted in Figure 6.

## 2.5 CHAPTER SUMMARY

This chapter has looked into the existing literature on the subject of the cause, development and outcome of WOM marketing, with a particular reference to WOM volume and WOM valence and the modeling of viral marketing. It has examined literature on WOM and viral marketing and then focused on literature regarding the modeling of WOM volume and WOM valence. Network topology models and artificial neural network models have been identified as the most appropriate approaches for the



modeling of WOM volume and WOM valence in viral marketing.

Variables have also been identified based on the literature to help the development of models which would assist researchers and marketers to predict WOM volume and valence outcome.

## **CHAPTER THREE**

### **RESEARCH OBJECTIVES AND METHODOLOGY**

#### **3.1 INTRODUCTION**

Burrell et al (1985) state that all theories should be based upon a philosophy of science and a theory of society. Consequently, the first section of this chapter will examine the different philosophical stances in social science directly relevant to this topic and to this investigation. It will discuss the philosophical positioning that is closely related to this research.

According to Berry (1983) research methodology is not just about data collection and the rules for evidence, it is more about the nature of explanation and the means by which explanations are produced. How knowledge is developed from these explanations depends upon the methodologies used. Research design on the other hand, provides the plan and structure as to how explanation could be obtained.

| <b>Main Objectives</b>  | <b>Methodologies/<br/>sections</b>             |
|---|--|
| Identify the significance of WOM and viral marketing research                   | Literature Review                              |
| Identify the most important WOM attributes for the modeling of viral marketing. | Literature Review                              |
| Examine previous literature regarding the cause of WOM                          | Literature Review                              |
| Examine previous literature regarding the development of WOM                    | Literature Review/<br>Methodology<br>Findings  |
| Examine previous literature regarding the outcome of WOM                        | Literature Review<br>Methodology               |
| Identify the method to model WOM volume and develop models                      | Literature Review/<br>Methodology/<br>Findings |
| Identify the antecedents of WOM valence in viral marketing                      | Literature Review<br>Methodology               |
| Select the modeling approach for WOM valence in viral marketing                 | Literature Review/<br>Methodology              |
| Develop models  | Literature<br>Review/Methodology/Findings      |

|   |             |
|---|-------------|
| Identify source of data and the<br>method to collect the data | Methodology |
|---|-------------|

Table 13 Main Objectives and Methodologies

### 3.2 PHILOSOPHICAL POSITIONING

Bilton et al (1987), state that different theorists tend to adapt different research methods in order to collate data to test their particular views on society. The question of whether some research methods are better than others is raised and there is no simple answer to this question. However, this thesis will take a contingency approach. After an investigation of a number of philosophical schools of thought it emerged that the Positivist Approach was most closely related to the philosophical positioning of this study.

In order to meet this aim, mathematical models would be proposed and will then be objectively tested. The following will now consider the main characteristics of Positivism and the criticisms, which have been raised against it by other philosophical social positions such as Interpretive, Phenomenological and Critical Theory.

Positivists argue that there is a truth or objective reality waiting to be discovered by social scientists. The researcher discovers this reality and the general causal laws that govern behaviour by staying detached, neutral and objective throughout the research (Bailey, 1996). The key idea of positivism argues that real knowledge should be based on facts (Comte, 1953) and derives after formulating and testing some research hypotheses (Easterby-Smith et al, 2002).

### 3.3 RESEARCH METHODOLOGY

#### 3.3.1 ESTIMATION OF DYNAMIC WOM VOLUME

#### DEVELOPMENT USING NETWORK TOPOLOGY MODELS

##### 3.3.1.1 INTRODUCTION OF COMPLEX NETWORKS

Traditionally the study of complex networks has been the territory of mathematics, especially the graph theory. Initially the graph theory focused on regular graphs, with no apparent design principles were described as random graphs, proposed as the simplest and most straightforward realisation of a complex network.

The pioneer of the theory was Leonhard Euler, who studied first regular

graphs in 18<sup>th</sup> century. In the 20th century the theory became much more statistically and algorithmically oriented. Later in 1950's graph theory was used to describe large networks, with no particular distributions of nodes and link, whose organisation principles were not easily definable. The computerisation of data acquisition has led to the emergence of large databases on the topology of various real networks. Wide availability of computer power allows to investigate networks containing millions of nodes, exploring questions that could not be answered before as well as the slow but noticeable breakdown between different science disciplines allows scientists to access different databases, allowing to uncover the generic properties of large networks.

The study of most complex networks has been initiated by a desire to understand various real systems. Complex systems that have been studied are:

|                         |   |
|-------------------------|---|
| World Wide Web<br>(WWW) | Nodes are web pages and links are hyperlinks. The network is directed, but in some researches is made undirected<br>Some of the researches are made on site level: All the pages in a site are merged into a supernode. |
|-------------------------|---|

|                                  |  |
|----------------------------------|--|
| Internet                         | Topology is studied at two different levels: at the router level the nodes are routers and edges are physical connections between them; at the interdomain level each domain, containing hundreds of routers, is represented as a single node. This is an undirected network.      |
| Cellular networks                | Metabolisms of different species from all three domains of life are studied and organised into networks in which the substrates (ATP, ADP, H <sub>2</sub> O) are nodes and edges represent the predominally directed chemical reactions in which these substrates can participate. |
| Ecological networks or food webs | The nodes are species and the edges represent predator-prey relationships among them. Food webs are directed networks  |
| Protein folding                  | Different states of single protein are represented by different nodes. Conformations are linked if they can be obtained from each other by an elementary move. This is an undirected network.  |
| Citation networks                | Published articles are represented by nodes and a directed edge represents a reference to a previously published article. This is an undirected network.   |

|                                    |   |
|------------------------------------|---|
| Co authorship networks             | Collaboration network exists of scientists represented by nodes and two nodes are connected if two scientists have written an article together.   |
| Movie actor collaboration networks | In this network the nodes are actors and two nodes have a common edge if two actors have acted in a movie together. This is an undirected network.  |
| The web of human sexual contacts   | Many sexually transmitted diseases spread on a network of sexual relationships. This is an undirected network.  |
| Phone-call networks                | A large directed graph can be constructed using telephone numbers as nodes and completed phone calls as edges, directed from caller to receiver.  |
| Networks in linguistics            | The complexity of human language offers several possibilities to define and study complex networks. One way of building a network is to describe words as nodes and connect them with edges if they appear one word form each other inside sentences of the literature of certain language. This is an undirected network. The other way to construct a network is to link words bases on their meaning: words are represented as nodes and are linked by an edge id they are known to be |



|                 |   |
|-----------------|---|
|                 | synonyms. This is an undirected network as well.  |
| Power networks  | Power grid is described as an undirected network where nodes are generators, transformers and substations and the edges are high-voltage transmission lines.              |
| Neural networks | Nerve systems of different animal species are studied. An undirected network nodes are neurons joined together by an edge if connected by either synapse or gap-junction. |

Table 14 Complex Systems that have been Studied

Studies of complex systems stated above were performed by different scientists on different datasets of different network sizes, ranging from small networks with only few hundred nodes (ecological networks) to large networks with as many as 109 nodes like WWW. Studied networks are of both directed and undirected type. In researches the average path length among the nodes of a graph, clustering coefficient and degree distribution were measured and compared to the same properties of random graphs. For a estimation of clustering coefficient the directed networks need to be turned into undirected, since coefficient can only be calculated for undirected webs. Most of the real networks feature short average path lengths, large clustering coefficients and many of them

have power-tail degree distribution and are scale free (WWW, cellular networks, Internet, some social networks and the citation networks).

Network is in mathematical terms represented by a graph, which is a pair of two sets  $G = \{P, E\}$ , where  $P$  is a set of  $N$  nodes and  $E$  is a set of edges (links, lines) that connect two elements of  $P$ .

|   |  |
|---|--|
| <b>Complex network</b><br><i>Networks below</i> | Research has been focused on the configuration of networks, including the degree distribution, the clustering coefficient, and the assortativity etc., which reveals that simple dynamical rules, such as preferential attachment or selective rewiring, can generate complex topologies (e.g. Albert and. Barabasi, 2002; Boccaletti et al, 2006; Lu et al., 2007; Chang et al., 2007). |
| <b>Small world network</b>                      | Constructed by adding links between randomly chosen nodes on networks in which nodes are connected to the nearest neighbors (Hsu et al., 2012)   |
| <b>Random network</b>                           | Nodes are connected with equal probability yielding a Poisson degree distribution (Faragó, 2011; McDonnell, et al., 2014)  |

|                           |  |
|---------------------------|--|
| <b>Scale-free network</b> | Small number of nodes have a very large number of links and large number of nodes have a small number of links such that the degree distribution follows a power law (Geoffrey and Ralph, 2015; Fortunato, Flammini and Menczer, 2006; FilippoMi et al., 2013) |
|---------------------------|--|

Table 15 Complex Networks

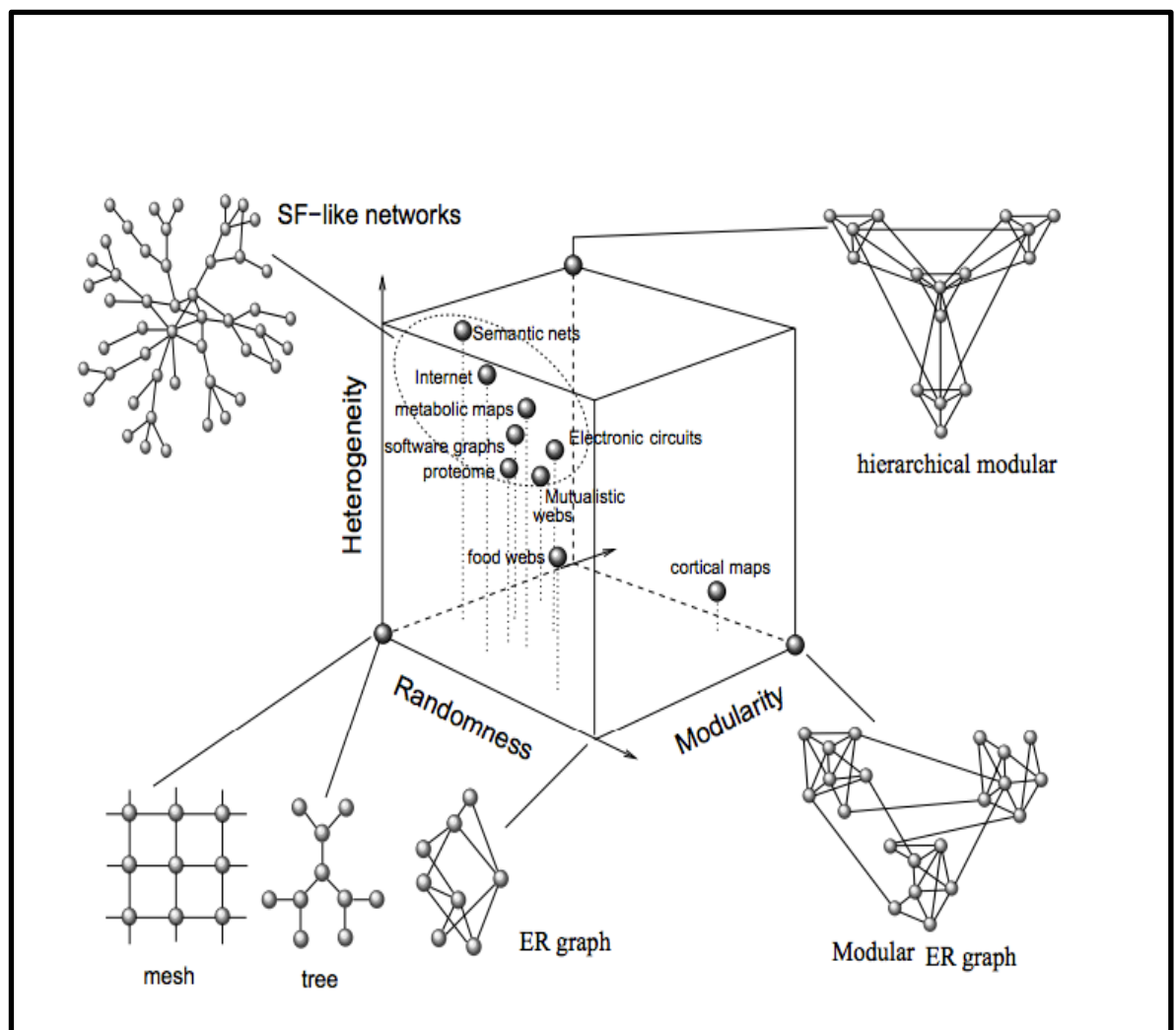


Figure 29 Topologies Features

### 3.3.1.2 SMALL WORLD NETWORKS

The small-world phenomenon (Milgram 1967; Pool and Kochen 1978) has long been an object of popular fascination and anecdotal report. The experience of meeting a complete stranger with whom we have apparently little in common and finding unexpectedly that we share a mutual acquaintance is one with which most of us are familiar-"It's a small world!" we say. More generally, most people have at least heard of the idea that any two individuals, selected randomly from almost anywhere on the planet, are "connected" via a chain of no more than six intermediate acquaintances, a notion made popular by the Broadway play (and later movie) *Six Degrees of Separation* (Guare 1990).

But is this phenomenon merely the confluence of unlikely coincidence and curious anecdote, or is it actually indicative of the underlying structure of modern social networks (Watts, 1999).

An explanation of the phenomenon, and more generally, a framework for examining the properties of networks consisting of very many components, is of general sociological interest: Many social metrics, such as status (Harary 1959; Burt 1982) and power (Coleman 1973), and

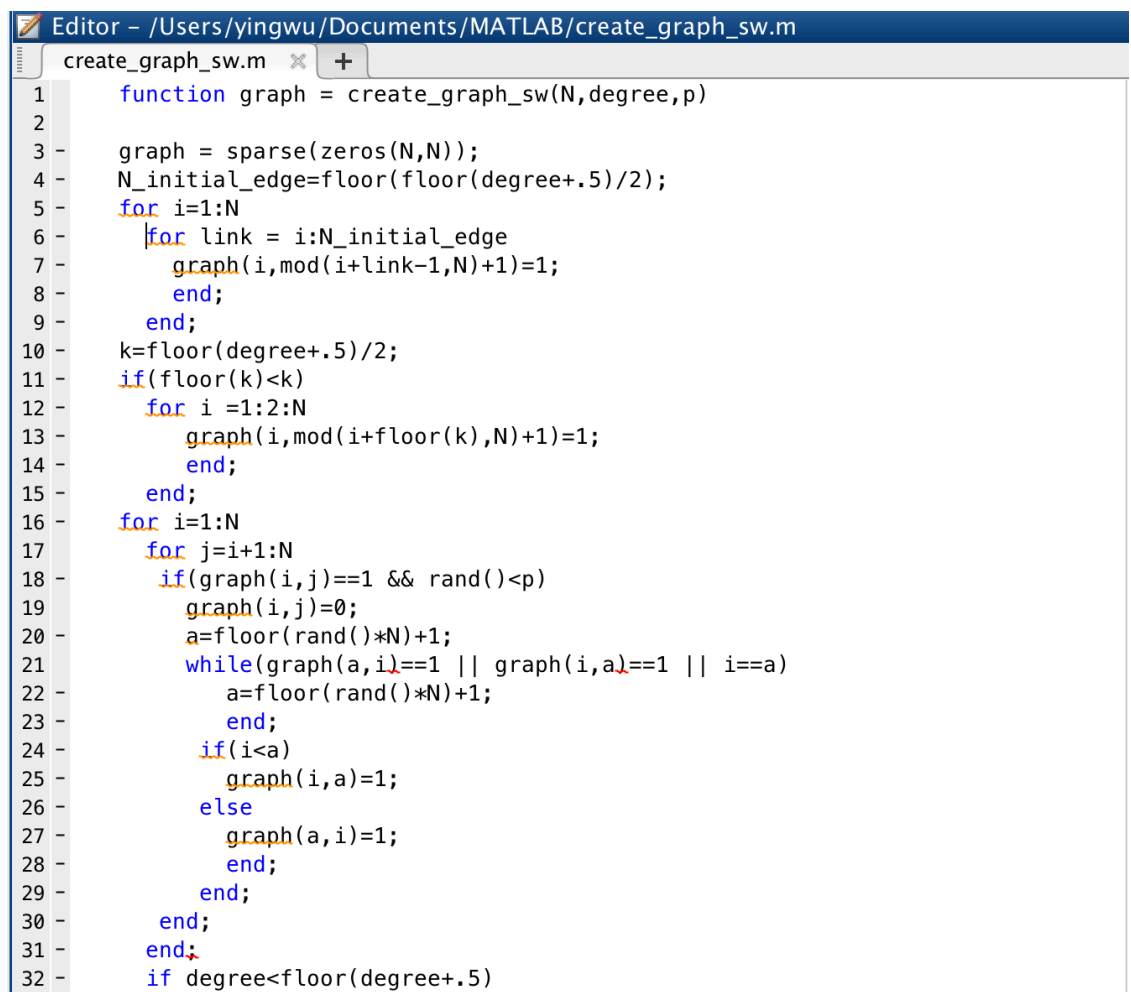
social processes, such as the diffusion of innovations (Rogers 1995) and transmission of influence (Friedkin 1990), are usefully represented in terms of networks of relationships between social actors, be they individuals, organizations, or nations. Indeed, the theory of social networks is one that has seen extensive development over the past three decades, yielding multiple measures both of individual significance, such as centrality (Freeman 1979, 1982; Friedkin 1991), and of network efficiency (Yamaguchi 1994a), which may elucidate nonobvious phenomena such as "key players" in an organization or its optimal structure for, say, information diffusion. Frequently, however, this research assumes linear models of social processes, such as Markov models of diffusion, and is generally applied to networks that consist of a relatively small number of components. While many of the measures defined in the literature can in principle be applied to networks of arbitrary size and structure, the computational costs of doing so may be prohibitive (such as for Freeman's [1979] betweenness centrality), and the benefits are at any rate unclear if the process of interest is inherently non-linear, as is the case for information (or disease) contagion models involving threshold (Granovetter 1978; Arthur and Lane 1993) or refractory (Murray 1993, chap. 19) effects. Hence, the problem of analyzing efficiently the structure of extremely large networks (in which components may easily number in the hundreds of thousands, or more),

and modeling the effects of structure on nonlinear dynamical processes, remains relatively unexplored.

Despite the large network size, it commonly happens that there is relatively short distance among any pair of nodes. Path length is defined by minimum number of edges needed to pass from first point to the other (in case of weighted edges, the path length is defined by minimal sum of weights). This phenomena is called the small world effect and can be observed in society and nature: all chemicals inside a living cell are at average 3 reactions away from each other, there is a path of acquaintances between most pairs of people in USA with typical length of about six and the actors in Hollywood are on average within three costars from each other. Despite the information shown above, the small world concept is not an indication of a special organising principle. The random graphs presented by Erdos and Reyni are the simplest network models to feature small world properties, since the typical distance among any two points in a random graph scales as  $\ln(N)$ , where  $N$  is a number of nodes in a network.

A small-world network is defined to be a network where the typical distance  $L$  between two randomly chosen nodes (the number of steps required) grows proportionally to the logarithm of the number of nodes  $N$  in the network,

$$L \propto \log N$$



```

Editor - /Users/yingwu/Documents/MATLAB/create_graph_sw.m
create_graph_sw.m
1 function graph = create_graph_sw(N,degree,p)
2
3 graph = sparse(zeros(N,N));
4 N_initial_edge=floor(floor(degree+.5)/2);
5 for i=1:N
6     for link = i:N_initial_edge
7         graph(i,mod(i+link-1,N)+1)=1;
8     end;
9 end;
10 k=floor(degree+.5)/2;
11 if(floor(k)<k)
12     for i = 1:2:N
13         graph(i,mod(i+floor(k),N)+1)=1;
14     end;
15 end;
16 for i=1:N
17     for j=i+1:N
18         if(graph(i,j)==1 && rand()<p)
19             graph(i,j)=0;
20             a=floor(rand()*N)+1;
21             while(graph(a,i)==1 || graph(i,a)==1 || i==a)
22                 a=floor(rand()*N)+1;
23             end;
24             if(i<a)
25                 graph(i,a)=1;
26             else
27                 graph(a,i)=1;
28             end;
29         end;
30     end;
31 end;
32 if degree<floor(degree+.5)

```

Figure 30 Small World Networks

The image shows a MATLAB Editor window with the title bar "Editor - /Users/yingwu/Documents/MATLAB/create\_graph\_sw.m". The window contains a script named "create\_graph\_sw.m" with the following code:

```
32 -     if degree < floor(degree + .5)
33 -         N_edge_removed = 0;
34 -         N_edge_to_remove = floor((floor(degree + .5) - degree) * N);
35 -         while(N_edge_to_remove > N_edge_removed)
36 -             for i = 1:N
37 -                 for j = i+1:N
38 -                     if(N_edge_to_remove > N_edge_removed && graph(i,j) == 1 &&
39 -                         rand() < N_edge_to_remove / (N_edge_per_vertice * N))
40 -                         graph(i,j) = 0;
41 -                         N_edge_removed = N_edge_removed + 2;
42 -                     end;
43 -                 end;
44 -             end;
45 -         end;
46 -     else
47 -         N_edge_added = 0;
48 -         N_edge_to_add = floor((degree - floor(degree + .5)) * N);
49 -         while(N_edge_to_add > N_edge_added)
50 -             for i = 1:N
51 -                 for j = i+1:N
52 -                     if(N_edge_to_add > N_edge_added && graph(i,j) == 0 &&
53 -                         rand() < N_edge_to_add / (N_edge_per_vertice * N))
54 -                         graph(i,j) = 1;
55 -                         N_edge_added = N_edge_added + 2;
56 -                     end;
57 -                 end;
58 -             end;
59 -         end;
60 -     end;
61 - end;
62 - graph = graph + graph';
```

Figure 31 Small World Networks (Continued.)

Figure 30 and Figure 31 have shown the construction of small world networks in MATLAB. There are  $N$  participants and once a participant re-tweet or re-blog a post, the relevant node degrees would be updated accordingly. The network construction process follows the small world rules. The construct of the network is dynamic and could be monitored over time.



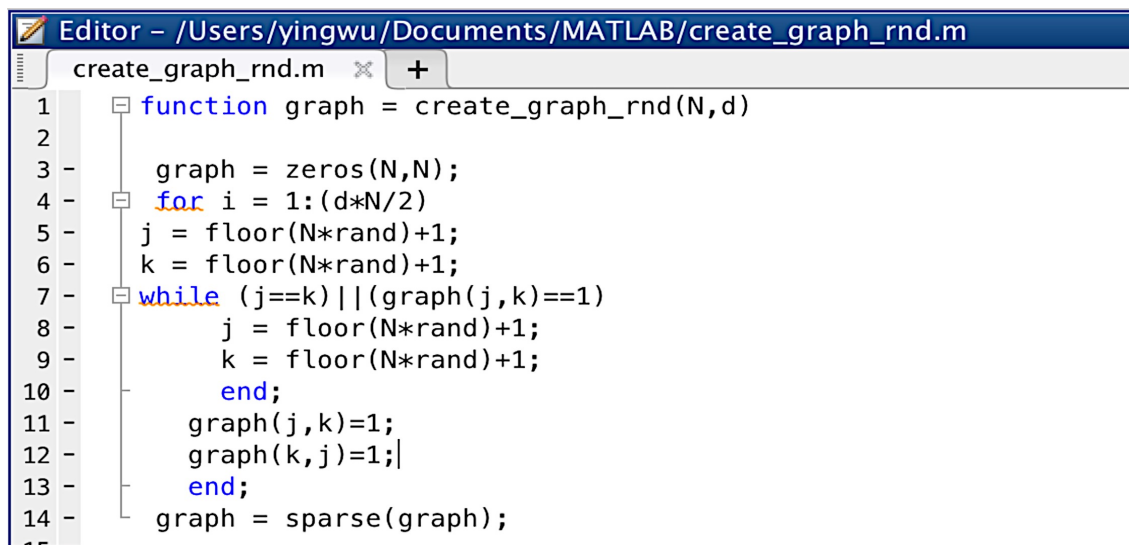
### 3.3.1.3 RANDOM NETWORKS

Starting with a set of  $N$  isolated vertices, the graph develops by the successive addition of random edges. The graphs obtained at different stages of this process correspond to larger and larger connection probabilities  $p$ , eventually obtaining a fully connected graph

$$p \rightarrow 1 \Rightarrow n = N \binom{N-1}{2}.$$

In a random graph with connection probability  $p$  the degree  $k_i$  of a node  $i$  follows a binomial distribution with parameters  $p$  and  $N-1$  :

$$P(k_i = k) = C_{N-1}^k p^k (1-p)^{N-1-k}$$



```

Editor - /Users/yingwu/Documents/MATLAB/create_graph_rnd.m
create_graph_rnd.m
1 function graph = create_graph_rnd(N,d)
2
3     graph = zeros(N,N);
4     for i = 1:(d*N/2)
5         j = floor(N*rand)+1;
6         k = floor(N*rand)+1;
7         while (j==k) || (graph(j,k)==1)
8             j = floor(N*rand)+1;
9             k = floor(N*rand)+1;
10        end;
11        graph(j,k)=1;
12        graph(k,j)=1;
13    end;
14    graph = sparse(graph);
15

```

Figure 32 Random Networks

#### 3.3.1.4 SCALE-FREE NETWORKS

Watts and Strogatz (1998) proposed a model where the connections between the nodes in a regular graph were rewired with a certain probability. The resulting graphs were between the regular and random in their structure and are referred to as small-world (SW) networks.

In many real examples of networks or graphs fully connected subgraphs emerge. Such structures are called cliques. A typical example of such feature are circles of friends or acquaintances in social networks where every member of a clique knows every other member. This inherent tendency of clustering is quantified by the clustering coefficient (Watts and Strogatz 1998) and is defined for a single node in the network:

$$C_i = \frac{2E_i}{k_i(k_i - 1)}$$

$E_i$  is the number of all edges that actually exist among all first neighbour of selected node. If all the neighbours were connected, there would be  $\frac{k_i(k_i - 1)}{2}$  edges among them. The ratio between the actual number of edges  $E_i$  and maximum number of edges is the clustering

coefficient of a node.

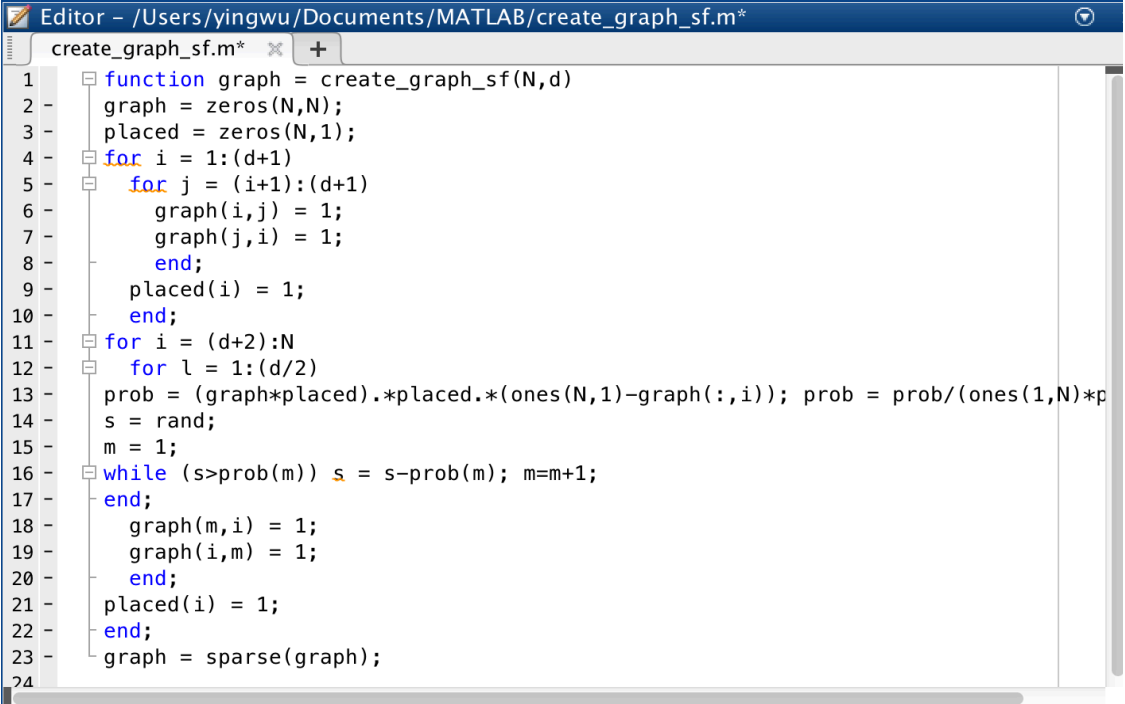
The clustering coefficient of all the network is the average of all individual

$$C = \frac{1}{N} \sum_{i=1}^N C_i$$

The number of edges a node has is called node degree. The spread of node degrees is characterised by a distribution function  $P(k)$ , which gives the probability that randomly selected node has exactly  $k$  edges. Since in the random graph the edges are placed randomly, the majority of nodes have approximately the same degree, close to the average  $\langle k \rangle$  of the network. The degree distribution of a random graph is a Poisson distribution  $P(k) = \frac{e^{-\langle k \rangle} \lambda^k}{k!}$  with a peak at  $P(\langle k \rangle)$ . On the other hand the empirical results for most large networks show distribution that significantly deviates from Poisson distribution. This degree distribution has a power-law tail:

$$P(k) \sim k^{-\gamma}$$

Such network are scale free. While some real networks still display an exponential tail, often the functional form of  $P(k)$  still deviates from Poisson distribution expected for a random graph.  $\gamma$  is an important parameter in defining the topology of a given network.



```

Editor - /Users/yingwu/Documents/MATLAB/create_graph_sf.m*
create_graph_sf.m*
1 function graph = create_graph_sf(N,d)
2     graph = zeros(N,N);
3     placed = zeros(N,1);
4     for i = 1:(d+1)
5         for j = (i+1):(d+1)
6             graph(i,j) = 1;
7             graph(j,i) = 1;
8         end;
9         placed(i) = 1;
10    end;
11    for i = (d+2):N
12        for l = 1:(d/2)
13            prob = (graph*placed).*(ones(N,1)-graph(:,i)); prob = prob/(ones(1,N)*p
14            s = rand;
15            m = 1;
16            while (s>prob(m)) s = s-prob(m); m=m+1;
17        end;
18        graph(m,i) = 1;
19        graph(i,m) = 1;
20    end;
21    placed(i) = 1;
22    end;
23    graph = sparse(graph);
24

```

Figure 33 Scale Free Networks

### 3.3.2 ESTIMATION OF DYNAMIC WOM VALENCE

#### DEVELOPMENT USING ARTIFICIAL NEURAL NETWORK MODELS

##### *Theoretical foundations of neural networks*

The types of neural networks we discuss are mathematical and computer models composed of simulated brain regions, or analogs of brain regions, and connections between them. The networks are designed with the goal of achieving with computer simulations some results that can be interpreted as analogous to some set of behavioral or neural or psychological data (Levine, 2000) . Neural network model construction sometimes goes “top down” from observed human or animal behavior. At other times it goes “bottom up” from the physiology of neurons comprising the brain. It can start either with psychological data or with neurobiological data, and is then often refined to make it fit better with the other type of data. The level of understanding that is reached is often sufficient to suggest experimental predictions at any of several levels (e.g., behavior—normal or pathological; single-neuron responses; neurochemistry; EEG recordings; or magnetic resonance imaging of brain regions). Grossberg (Grossberg, 1971; Grossberg, 1975) developed a modeling framework for classical conditioning (also, in

(Grossberg, 1971) , including operant or Skinnerian conditioning, the learning of rewarded responses). The neural network of Grossberg (1971) included drive nodes in addition to sensory and motor nodes. The idea was that, for example, a dog learning to associate the sound of a bell with salivation is not learning an association of a stimulus with a specific behavioral response, but rather a more general association of a stimulus (bell) with satisfaction of an internal drive (hunger).

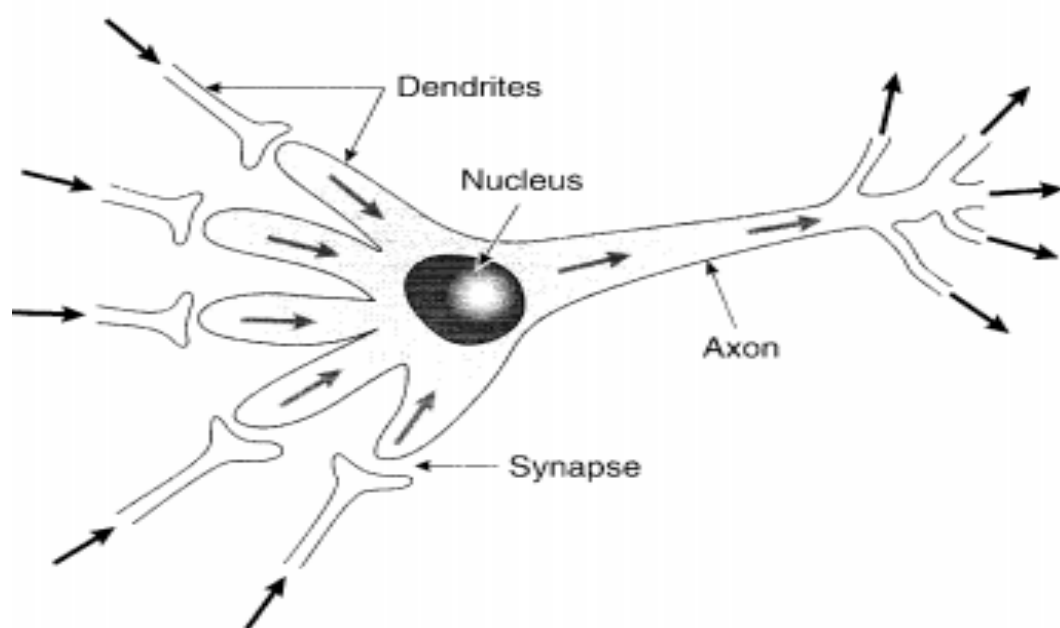


Figure 34 Structure of Biological Neuron

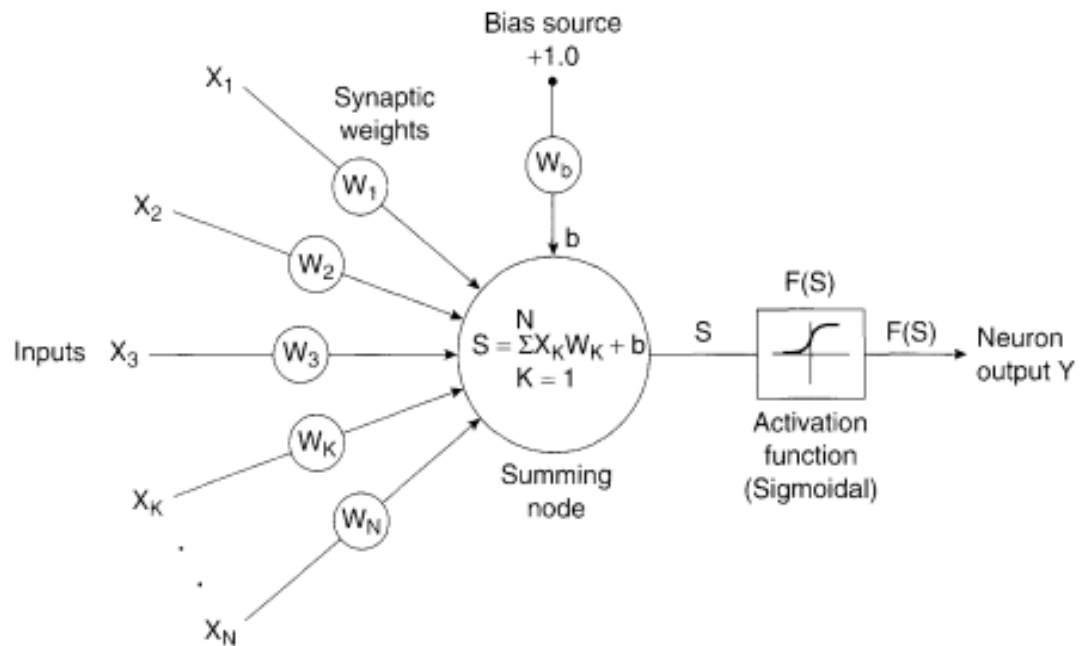


Figure 35 Structure of ANN

Nodes are most often identified with large groups of neurons or with brain regions, whose boundaries may not yet be precise. Sometimes, in fact, nodes are interpreted as representations of psychological entities (stimuli, drives, etc.) whose location in the brain might or might not be specified. However, even though nodes seldom represent individual neurons, there are many models wherein some node activity patterns are similar to single-neuron electrical activity patterns in some brain regions relevant for the behavior being modeled.

In the late 1960s, several modelers began to develop principles for fitting biologically relevant neural network architectures to specific

cognitive and behavioral functions. This led to models requiring partial verification on both the physiological and the behavioral levels, and a “toolkit” of modeling techniques and modules still in wide use.

In particular, Stephen Grossberg and his colleagues (Grossberg, 1982 ) developed differential equations using two sets of variables: node activities and connection weights , which were inspired by the psychologist Clark Hull’s previous notions of stimulus trace and associative strength (Hull, 1943) . For each stimulus  $A$  , the stimulus trace  $x_A(t)$  measures how active the memory for  $A$  is at any given time  $t$  . For each pair of stimuli  $A$  and  $B$  , the associational strength  $\omega_{AB}(t)$  measures how strong the sequential association  $AB$  is in the network’s memory at time  $t$  . Node activities are analogous to short-term memory (STM) and connection weights are analogous to long-term memory (LTM). The decay rate for LTM traces is set much smaller than the decay rates for STM traces.

An example of the equations Grossberg developed can be seen in a simple network called the outstar (Grossberg, 1968). The outstar was one of the first networks to learn distributed patterns, and was later used as a component in more complex multilevel categorization networks



(Carpenter and Grossberg, 1987) . In an outstar, one node (or vertex, or cell population)  $v_1$  , called a source , projects to other nodes  $x_2$ ,  $x_3, \dots, x_n$  , called sinks. The relative proportions of sink node activities are interpreted as a spatial pattern, and Grossberg proved theorems indicating under what conditions those proportions converge as time gets large to the pattern of inputs to those nodes. The outstar is a good illustration of the general method because it is a component of larger networks designed to perform various psychological tasks, including those involved in both classical conditioning and categorization.

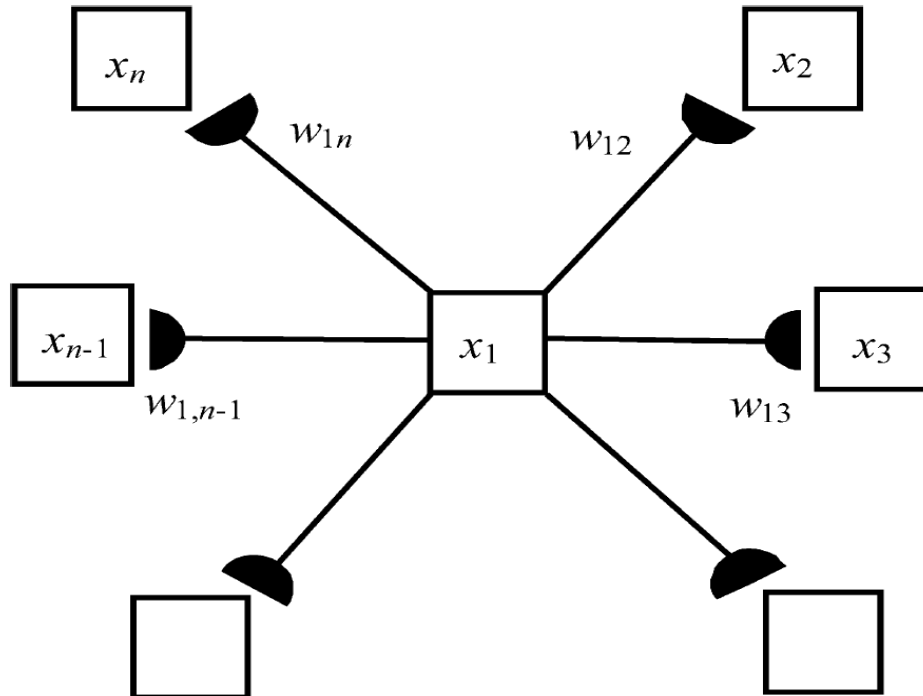


Figure 36 Outstar architecture. (Squares denote nodes. Semicircles denote modifiable excitatory connections.)

For the outstar, denote the source node activity by  $x_1$ ; the sink node activities by  $x_2, x_3, \dots, x_n$ ; the learnable source-to-sink weights by  $\omega_2, \omega_3, \dots, \omega_n$ , the (time-varying) input to the source node by  $I_1$  and the (time-varying) inputs to the sink nodes by  $I_2, I_3, \dots, I_n$ . Then in one version of the theory, the node activities and weights change over time according to the following system of nonlinear differential equations

$$\frac{dx_1}{dt} = -\alpha x_1 + I_1$$

$$\frac{dx_i}{dt} = -\alpha x_i + b x_1 \omega_{1i}, \quad i = 2, \dots, n,$$

$$\frac{d\omega_{1i}}{dt} = x_1 - (-c\omega_{1i} + x_i), \quad i = 2, \dots, n,$$

where  $a$ ,  $b$ , and  $c$  are positive constants and  $c$  is much smaller than  $a$ , indicating that LTM decay is much slower than STM decay. With this background we can proceed to discuss models of classical conditioning (also known as Pavlovian conditioning), the type of

learning that occurred when Ivan Pavlov trained dogs to salivate to the sound of a bell after many pairings of the bell with food.

The neural network of Grossberg (1971) included drive nodes in addition to sensory and motor nodes. The idea was that, for example, a dog learning to associate the sound of a bell with salivation is not learning an association of a stimulus with a specific behavioral response, but rather a more general association of a stimulus (bell) with satisfaction of an internal drive (hunger).

Sutton and Barto (Sutton and Barto, 1988) modeled some classical conditioning data with a theory that included elements of both the Rescorla–Wagner and Klopff theories. Their conditioning model includes  $n$  stimulus traces  $x_i(t)$ , an output signal  $y(t)$ , and  $n$  connection weights  $w_i(t)$ . These weights are considered to denote associations between conditioned stimuli (labeled CS) and a primary reinforcer or unconditioned stimulus (labeled US). Learning is assumed to occur at discrete time steps, leading to difference equations.

Sutton and Barto proposed that in addition to the stimulus traces which denote the duration and intensity of given CSs, there are

additional traces that are separate from the stimuli and longer lasting. These are the actual short-term memory traces, but Sutton and Barto termed them eligibility traces because they indicate when a particular synapse is eligible for modification. Possible cellular mechanisms were suggested for eligibility traces, involving calcium ions and cyclic nucleotides. Finally, the current amount of reinforcement,  $y(t)$ , was compared with the weighted average of values of  $y$  over some time interval preceding  $t$ . This led to the following system of equations relating the CS node activities  $x_i(t)$ , output activity  $y(t)$ , CS-to-output weights  $w_i(t)$ , eligibilities  $\bar{x}_i(t)$  and ongoing output level  $\bar{y}(t)$  (representing a weighted average of past output activities):

$$\bar{x}_i(t+1) = \alpha \bar{x}_i(t) + x_i(t)$$

$$\bar{y}(t+1) = \beta \bar{y}(t) + (1 - \beta) y(t)$$

$$w_i(t+1) = w_i(t) + c(y(t) - \bar{y}(t)) \bar{x}_i(t)$$

$$y(t) = f \left[ \sum_{j=1}^n w_j(t) x_j(t) + w_0(t) x_0(t) \right]$$

where  $y(t)$  is bounded to remain in the interval  $[0, 1]$  (that is, replaced by 1 if it gets above 1), and  $\beta$  are constants between 0 and 1;  $f$  is a sigmoid function,  $c$  is a positive constant determining the rate of learning; and  $x_0(t)$  and  $w_0(t)$  are the activity and associative strength of the US trace. The two innovations in Sutton and Barto's model—eligibility traces and learning dependent on change in postsynaptic activity—were motivated by results on timing in classical conditioning. In particular, the model was designed to explain the fact that in many conditioning paradigms, the optimal interstimulus interval (defined as the time delay between CS presentation and US presentation) is greater than 0. Sutton and Barto's network can also simulate other contextual effects in classical conditioning, such as the blocking paradigm mentioned earlier.

Sutton and Barto's work was elaborated by Klopff (1988) and others into the differential Hebbian learning rule (also called the drive-reinforcement rule), whereby connection weights from one node to another change as a function of changes over time in both node activities. Klopff was led to such a rule by his earlier hedonistic neuron theory in which neurons themselves were goal-seeking. Klopff's network simulated a wide variety of classical conditioning

data. These data included blocking, secondary conditioning, extinction and reacquisition of an extinguished response, conditioned inhibition, effects of interval between CS and US occurrences, effects of stimulus durations and amplitudes. However, the simulations of CS-US interval effects depend on some weighting factors for time delays, factors that were chosen specifically to match those data, and not generated by an underlying neural mechanism.

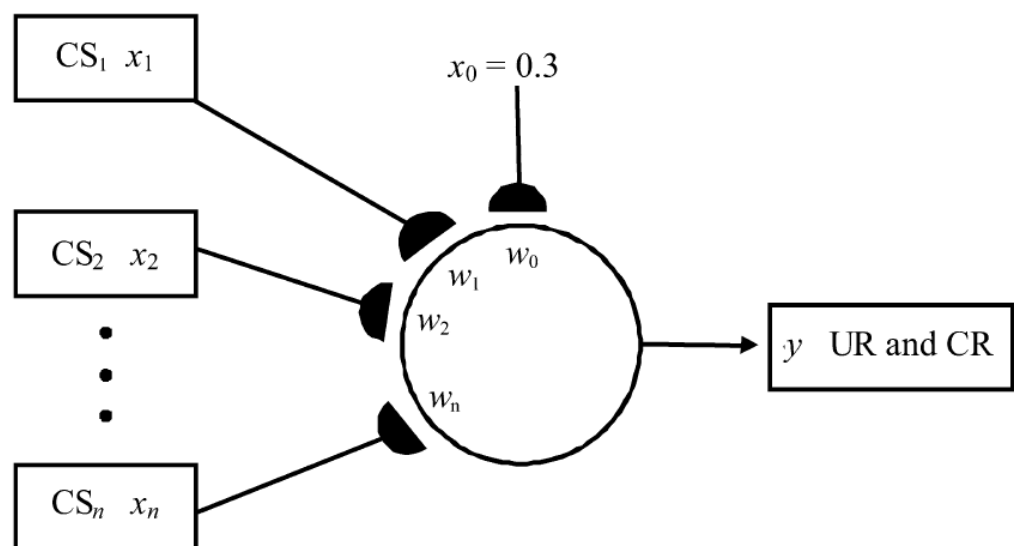


Figure 37 The CS-US Neuron

Note: Network with  $n$  learnable conditioned stimulus (CS) pathways, and a pathway with fixed weight  $w_0$  for the unconditioned stimulus (US). The node  $y$  represents unconditioned conditioned responses (UR and CR).

The learning law involving change in postsynaptic activity is not the only possible way to simulate timing effects or blocking in classical conditioning. The same data were simulated by Grossberg and Levine (1987) using a form of the earlier Grossberg learning law based on associative learning combined with attentional effects, due to lateral inhibition, in a larger network.

Recent brain imaging and evoked potential studies have shed further light on the neural bases for the different roles of emotion. In particular, there are many results on how the amygdala and different parts of the cortex and thalamus process emotional versus nonemotional stimuli.

Most of the research done so far on neural network modeling of emotion has differentiated positive versus negative affect, but otherwise has been relatively nonspecific. Neural network modeling of specific emotions (fear, sadness, joy, disgust, anger, surprise, etc.) is just starting to emerge.

Emotional stimuli for positive/negative WOM valence in WOM campaigns, in the context of this thesis, are the factors boost emotional reactions to products/services (i.e. factors that represent

emotional significance (either positively or negatively). Based on the previous literature review (Chapter 2), there are six factors that have been proved to be significant towards WOM valence.

|       |                     |  |
|-------|---------------------|--|
| $I_1$ | <b>Satisfaction</b> | A measure of how the experience with a firm, its products, its services (ratings) meets or exceeds customer satisfaction expectation (e.g. Endo, Yang, and Park, 2012; Tsao and Hsieh, 2012; Young and Hyunjoo, 2012; Liu, et al., 2013)   |
| $I_2$ | <b>Loyalty</b>      | An intention to perform a diverse set of behaviors that signal a motivation to maintain a relationship with the focal firm, including allocating a higher share of the category wallet to the specific service provider, engaging in positive word of mouth (WOM), and repeat purchasing (e.g. Gruen, Osmonbekov and Czaplewski, 2006; Lee, Noh and Kim, 2013; |



|       |                   |   |
|-------|-------------------|---|
|       |                   | Berezan, et al. 2015)   |
| $I_3$ | <b>Quality</b>    | The ability to meet or exceed customer's expectations. (e.g. Tsao and Hsieh, 2012; Choi, 2013; Heyes and Kapur, 2012; Lai et al., 2010; Gupta and Harris, 2010) |
| $I_4$ | <b>Commitment</b> | An enduring desire to maintain a valued relationship (e.g. Tsao and Hsieh, 2012; Berezan, et al. 2015; Wolny and Mueller, 2013; Wen and Cheng, 2013)            |
| $I_5$ | <b>Trust</b>      | A willingness to rely on an exchange partner in whom one has confidence. (e.g. Lin, Lu and Wu, 2012; Lee, 2014; See-To and Ho, 2014)                            |

|       |                        |  |
|-------|------------------------|--|
| $I_6$ | <b>Perceived value</b> | The value that a product or service has in the mind of the consumer. (e.g. Ha and Im, 2012; Jalilvand and Samiei, 2012; Hsu, Lin and Chiang, 2013; Gruen, Osmonbekov and Czaplewski, 2006) |
|-------|------------------------|--|

Table 16 Input Stimuli for ANN

### *Multi-layer perceptron artificial neural networks*

Among various types of neural networks, MLP ones are probably the most extensively applied to a variety of problems. Although considering MLP networks as universal approximators (Hornik et al., 1989) based on Kolmogorov's superposition theorem is disputable (Hecht-Nielsen, 1987; Girosi and Poggio, 1989; Nakamura et al., 1993; Braun and Griebel, 2009), they are still widely accepted as a useful tool to deal with a number of real world regression problems. In general, MLP is a nonlinear data-based model that approximates the values of output variables (y) dependent on the set of input variables (x). In the present paper the single output is considered – 1 day ahead runoff forecast at Wilmot, Nova Scotia. MLP is formed by several nodes arranged in groups called layers. The most popular and the simplest MLP consist of

three layers, an input layer, a hidden layer, and an output layer.

WOM valence modeling by means of ANN requires the selection of the set of input variables  $x$  from the available data and the appropriate number of hidden nodes.

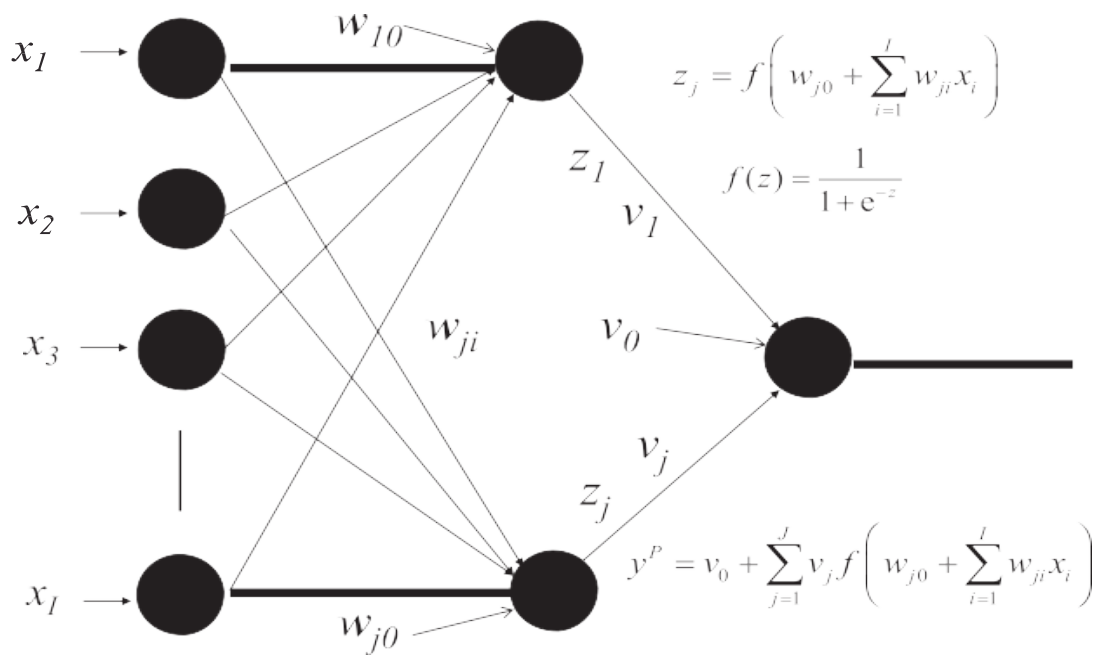


Figure 38 Scheme of Multi-Layer Perceptron Neural Network

Notes:  $x_i$  are input variables,  $I$  is number of input nodes,  $J$  is number of hidden nodes,  $w_{ji}$  and  $v_j$  are neural network weights, and  $y^P$  is output value of searched variable.

The classical MLP for WOM Valence is defined as follows. The nodes are linked via weighted connections  $w$  and  $v$ . The values of these connections are adaptively modified during the process of training. Each

node performs a weighted sum of its inputs and filters it through the so-called activation function. A few popular activation functions are well described in the literature (Haykin, 1999). In this study widely used sigmoidal function is applied in the hidden layer:

$$f(z_j) = \frac{1}{1 + e^{-z_j}}$$

where  $z_j$  is the weighted sum of  $I$  input variables  $x_i$

$$z_j = f\left(w_{j0} + \sum_{i=1}^I w_{ji}x_i\right)$$

Then the weighted  $z_j$  multiplied by proper weights  $v_j$  and then transferred to the neuron of the third (output) layer, where the new weighted sum is computed, giving finally:

$$y^p = v_0 + \sum_{j=1}^J v_j f\left(w_{j0} + \sum_{i=1}^I w_{ji}x_i\right)$$

where  $J$  is the number of hidden nodes and  $y^p$  is the estimated value of dependent variable  $y$ . After re-standardization of  $y^p$ , the predicted

WOM valence value is obtained.

The popular Mean Square Error (MSE) function is applied in the present research

$$J(w,v) = \min_{w,v} \frac{1}{K} \sum_{k=1}^K \left( y_k^p(w,v) - y_k \right)^2$$

where K is the number of data within particular data set (training, validation or testing). Two factors usually make the training difficult—multimodality of the objective function and overfitting –e.g. fitting the model parameters to both signal and noise (or errors) presented in the training data set. A number of methods have been developed to avoid overfitting or limiting the generalization capacity of the ANN, including early stopping, weight decay, noise injection or Bayesian approach (Holmstrom and Koistinen, 1992; Reed et al., 1995; Haykin, 1999; Pierce et al., 2006; Zur et al., 2009).

### 3.3.3 SAMPLING METHODS AND DATA SOURCING

#### *Web crawling: an introduction with an example (twitter)*

Web Data Extraction systems are a broad class of software applications targeting at extracting data from Web sources (Laender et al., 2002; Baumgartner, Gatterbauer, and Gottlob G., 2009). A Web Data Extraction system usually interacts with a Web source and extracts data stored in it: for instance, if the source is an HTML Web page, the extracted content could consist of elements in the page as well as the full-text of the page itself. Eventually, extracted data might be post-processed, converted in the most convenient structured format and stored for further usage (Irmak and Suel., 2006; Zhao, 2004)

Web Data Extraction systems find extensive use in a wide range of applications including the analysis of text-based documents available to a company (like e-mails, support forums, technical and legal documentation, and so on), Business and Competitive Intelligence (Baumgartner et al., 2005), crawling of Social Web platforms (Catanese, 2011; Gjoka et al., 2012), Bio-Informatics (Plake et al., 2006) and so on. The importance of Web Data Extraction systems depends on the fact that

a large (and steadily growing) amount of data is continuously produced, shared and consumed online: Web Data Extraction systems allow to efficiently collect these data with limited human effort. The availability and analysis of collected data is an infeasible requirement to understand complex social, scientific and economic phenomena which generate the data. For example, collecting digital traces produced by users of Social Web platforms like Facebook, YouTube or Flickr is the key step to understand, model and predict human behavior (Kleinberg, 2000; Newman, 2003; Backstrom et al., 2011).

In the commercial field, the Web provides a wealth of public domain information. A company can probe the Web to acquire and analyze information about the activity of its competitors. This process is known as Competitive Intelligence (Chen et al., 2012; Zanasi, 1998) and it is crucial to quickly identify the opportunities provided by the market, to anticipate the decisions of the competitors as well as to learn from their faults and successes.

The design and implementation of Web Data Extraction systems has been discussed from different perspectives and it leverages on scientific methods coming from various disciplines including Machine Learning, Logic and Natural Language Processing.

In the design of a Web Data Extraction system, many factors must be taken into account; some of them are independent of the specific application domain in which we plan to perform Web Data Extraction. Other factors, instead, heavily depend on the particular features of the application domain: as a consequence, some technological solutions which appear to be effective in some application contexts are not suitable in others. In its most general formulation, the problem of extracting data from the Web is hard because it is constrained by several requirements. The key challenges we can encounter in the design of a Web Data Extraction system can be summarized as follows:

Web Data Extraction techniques implemented in a Web Data Extraction system often require the help of human experts. A first challenge consists of providing a high degree of automation by reducing human efforts as much as possible. Human feedback, however, may play an important role in raising the level of accuracy achieved by a Web Data Extraction system. A related challenge is, therefore, to identify a reasonable tradeoff between the need of building highly automated Web Data Extraction procedures and the requirement of achieving accurate performance.



Web Data Extraction techniques should be able to process large volumes of data in relatively short time. This requirement is particularly stringent in the field of Business and Competitive Intelligence because a company needs to perform timely analysis of market conditions.

Applications in the field of Social Web or, more in general, those dealing with personal data must provide solid privacy guarantees. Therefore, potential (even if unintentional) attempts to violate user privacy should be timely and adequately identified and counteracted.

Approaches relying on Machine Learning often require a significantly large training set of manually labeled Web pages. In general, the task of labeling pages is time-expensive and errorprone and, therefore, in many cases we cannot assume the existence of labeled pages.

Oftentimes, a Web Data Extraction tool has to routinely extract data from a Web Data source which can evolve over time. Web sources are continuously evolving and structural changes happen with no forewarning, thus are unpredictable. Eventually, in real-world scenarios it emerges the need of maintaining these systems, that might stop working correctly if lacking of flexibility to detect and face structural modifications of related Web sources.

The theme of Web Data Extraction is covered by a number of reviews. Laender et al. (Laender et al., 2002) presented a survey that offers a rigorous taxonomy to classify Web Data Extraction systems. The authors introduced a set of criteria and a qualitative analysis of various Web Data Extraction tools.

Kushmerick (Kushmerick, 2002) defined a profile of finite-state approaches to the Web Data Extraction problem. The author analyzed both wrapper induction approaches (i.e., approaches capable of automatically generating wrappers by exploiting suitable examples) and maintenance ones (i.e., methods to update a wrapper each time the structure of the Web source changes). In that paper, Web Data Extraction techniques derived from Natural Language Processing and Hidden Markov Models were also discussed. On the wrapper induction problem, Flesca et al. (Flesca, 2004) and Kaiser and Miksch (Kaiser, and Miksch, 2005) surveyed approaches, techniques and tools. The latter paper, in particular, provided a model describing the architecture of an Information Extraction system. Chang et al. (2006) introduced a tridimensional categorization of Web Data Extraction systems, based on task difficulties, techniques used and degree of automation. In 2007, Fiumara applied these criteria to classify four state-of-the-art Web Data

Extraction systems. A relevant survey on Information Extraction is due to Sarawagi (2008). Recently, some authors focused on unstructured data management systems (UDMSs) (Doan, et al., 2009) i.e., software systems that analyze raw text data, extract from them some structure (e.g. person name and location), integrate the structure (e.g., objects like New York and NYC are merged into a single object) and use the integrated structure to build a database. UDMSs are a relevant example of Web Data Extraction systems and the work from Doan et al. (2009) provides an overview of Cimple, an UDMS developed at the University of Wisconsin.

In the latest years, Social Web platforms emerged as one of the most relevant phenomenon on the Web: these platforms are built around users, letting them to create a web of links between people, to share thoughts, opinions, photos, travel tips, etc. In such a scenario, often called Web 2.0 users turn from passive consumers of contents to active producers. Social Web platforms provide novel and unprecedented research opportunities.

Twitter.com (<http://twitter.com/>) is a online social network used by millions of people around the world to stay connected to their friends, family members and co-workers through their computers and mobile

phones. The interface allows users to post short messages (up to 140 characters) that can be read by any other Twitter user. Users declare the people they are interested in following, in which case they get notified when that person has posted a new message. A user who is being followed by another user does not necessarily have to reciprocate by following them back, which makes the links of the Twitter social network directed.

Web crawler (also known as a Web spider or Web robot) is a program or automated script which browses the World Wide Web in a methodical and automated manner. Hyperlinks interconnect webpages and therefore the information across the Web, forming the underlying concept of hypertext which defines the structure of the Web and makes Web browsing possible. This Web hypertextual environment can be modeled as a directed, connected and sparse graph whose vertices correspond to webpages and edges correspond to hyperlinks that interconnect them (Brodera et al., 2000 ; Cooper and Frieze, 2001 ; Cooper and Frieze, 2002; Manning, Raghavan, and Schütze , 2008).

Previous studies (Davison, 2000; Craswell, Hawking, and Robertson, 2001) have shown important properties of the linkage structure of the webgraph, as summarized below:

- webpages that are linked to each other within the webgraph have a recommendation relation as the author of the source webpage referenced the target webpage by using a hyperlink;
- webpages that are linked to each other within the webgraph are likely to have related or similar content
- hyperlink text (also known as anchor text) of a source webpage usually describes the target webpage to which it is linked to.

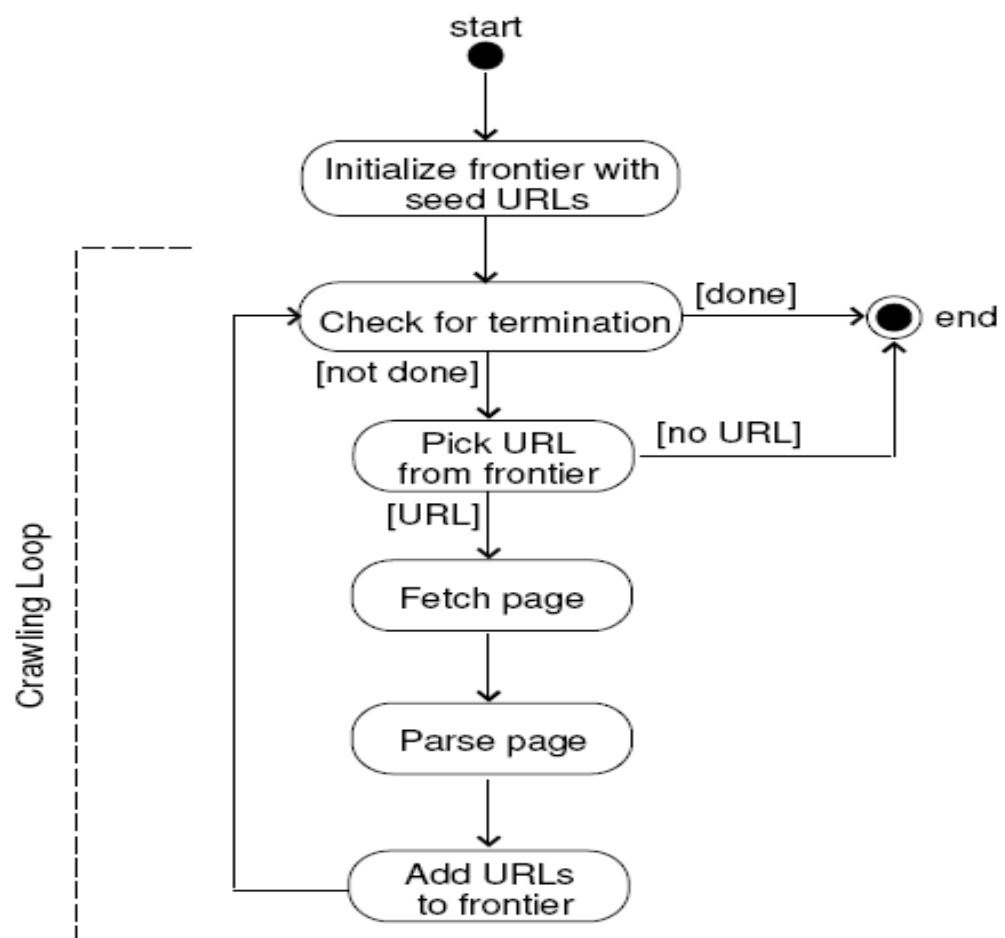


Figure 39 Web Crawling

### *Data crawling tools in Twitter*

Bosnjak et al. presented an open source crawler, TwitterEcho, which is used to retrieve data from Twitter (Twitter, 2013; Bosnjak et al. , 2012). It allows data seekers to collect data from a focused community of interest. TwitterEcho adapts a centralized distributed architecture and includes three main components: clients, servers, and modules. A client consists of two modules. The first module collects tweets, user profiles, and simple statistics. The second module collects social network relations. The number of clients can be increased to retrieve more data from Twitter. The server manages the crawling process and allocation of user lists to each client. It also maintains the database in which the downloaded data is saved. Modules consist of user expansion, user selection, and user inspection. The user expansion module analyzes downloaded tweets, extracts the user's mentions, and adds the user's followers to the list of tentative users. The user selection module identifies users' accounts to be monitored by analyzing profiles and identifying languages. The user inspection module also monitors events, such as deletion, suspension, and the activity of users' accounts.

Another approach to collecting Twitter data is the use of the computation power of cloud computing (Noordhuis et al. , 2010).

Noordhuis et al. gathered Twitter data and applied the PageRank algorithm to rank Twitter users using the computation power of cloud computing. There were five steps in this cloud system. First, a queue and table are set up to maintain all user IDs that need to be crawled. Then, users' and followers' IDs are saved in the SimpleDB, which is a service for storing structured data in the cloud. Furthermore, different users' information is gathered for different instances simultaneously by using their own web service. In the fourth step, the PageRank Algorithm is applied to rank users. Finally, a web interface enables public users to access their data.

Kwak et al. gathered Twitter data to study the topological characteristics of Twitter and its power for information sharing (Kwak et al. , 2010). By using Twitter APIs, they gathered all users' profiles, trending topics, and tweets that mentioned the trending topics. As a result, they successfully crawled the entire Twitter site, including 41.7 million user profiles, 1.47 billion social relations, 4,262 trending topics, and 106 million tweets.

Analyzing sentiment of messages in social networks has been studied in various ways. Dey and Haque proposed a localized linguistic approach to extract opinion expressions from noisy text that are generated from

online chat, emails, blogs, customer feedback, and reviews (Dey and Haque, 2008). Based on the pre-processed noisy texts, they analyzed opinion expressions using a classifier algorithm and candidate opinion words from Wordnet. Hu and Liu suggested a technique to identify opinion sentences in each review about product features and to decide whether each opinion sentence is positive and negative (Hu and Liu, 2004). They determine its semantic orientation using a set of adjective words, which are identified by a natural language processing. O'Connor et al. presented an approach to polarity classification by counting the number of positive and negative expressions in a tweet and selecting the category with more terms (O'Connor et al. , 2010) Label propagation using graph-based methods can also be used to find opinion from social network sites (Zhu and Ghahramani, 2002; Baluja et al. , 2008; Talukdar and Crammer, 2009). Choi and Cardie used domain specific lexicon and relations among words and opinion expressions to classify polarity of messages in a social network site (Choi and Cardie, 2009). However, the accuracy for polarity classification still needs to be improved as the accuracy in other research shows polarity classification of 80 percent.



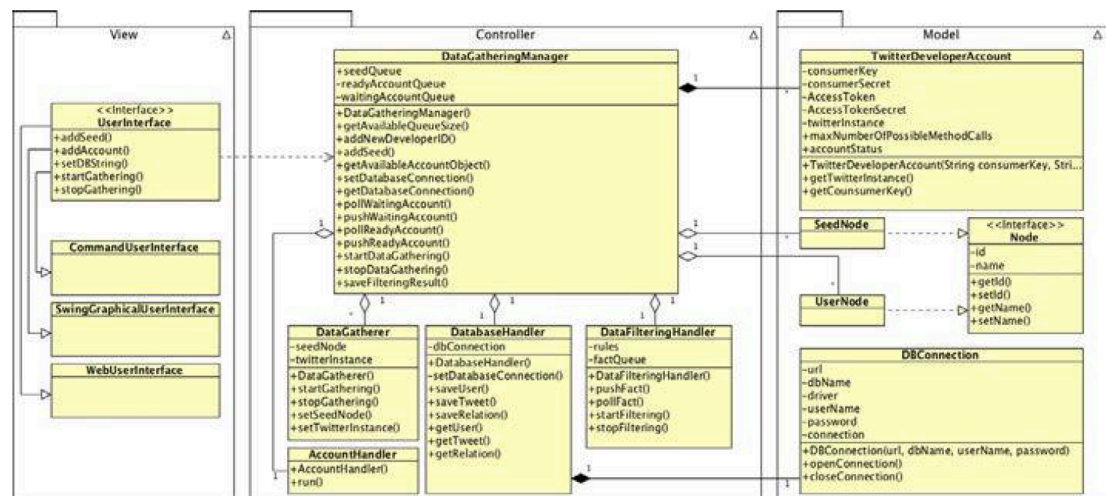


Figure 40 Diagram of the Twitter Data Collecting Tool

Before the analysing process of twitter data, the target data set must be collected. Twitter enables researchers and data analysers to access data in Twitter by providing application programming interface (API). Figure 39 is a Unified Modeling Language (UML) diagram that visualises the data collection program and it illustrates the twitter data collecting tool that crawls data through twitter APIs. The Twitter Data Collecting Tool is applied to gather requested data from Twitter. The crawler starts with a seed node and keeps inspecting its followers and their followers' data.

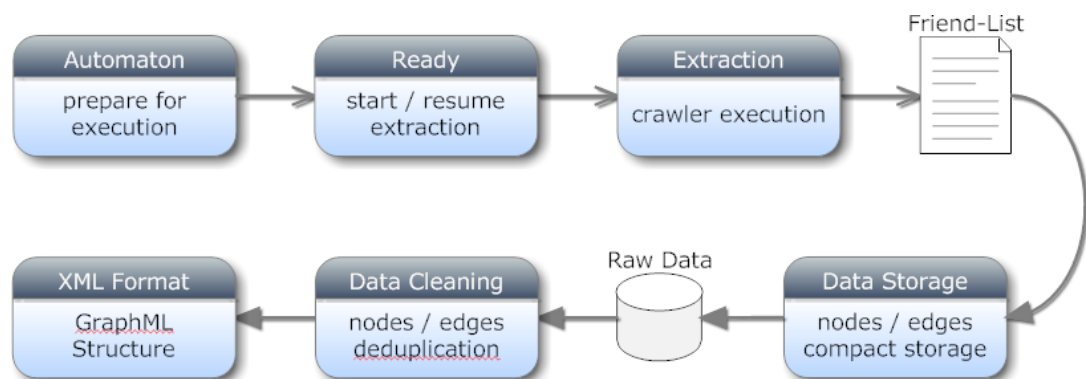


Figure 41 Flow of Topology Extraction

Figure 41 illustrates the process of automated extraction from user profiles on online social networking sites that results in the construction of corresponding network topologies. This extraction strategy gets applied in the topology extractions of weibo and twitter (Table 17) to support the EWOM volume development simulations.

First, the process starts with a user's input from a user interface. A user enters seed node IDs, Twitter developer account information, and filtering keywords in the user interface. Once the user enters the input, it invokes the `DataGatheringManager` class. Then, the `DataGatheringManager` class executes the `DatabaseHandler` class, the `DataFilteringHandler` class, the `AccountHandler` class to set up a database connection and options for gathering and filtering. Based on the connection and gathering options, the `DataGatherer` class gathers users, relation and tweets data from Twitter and save them in a designated

database. Finally, the DataFilteringHandler class filters the tweets using the keywords. The gatherin process ends when the user calls stopGathering( ) method from user interface.

Good URLs can induce the good searchresult in search engine. It verifies that selecting seed URLs accordingto the user's query topic plays an important role in traversing theWeb for the focused web crawler.

*Data Sourcing of Twitter and Weibo (China's version of twitter),*

|         |  |
|---------|--|
| Twitter | Twitter.com ( <a href="http://twitter.com/">http://twitter.com/</a> ) is a online social network used by millions of people around the world to stay connected to their friends, family members and co-workers through their computers and mobile phones. The interface allows users to post short messages (up to 140 characters) that can be read by any other Twitter user. Users declare the people they are interested in following, in which case they get notified when that person has posted a new message. A user who is being followed by another user does not necessarily have to reciprocate by following them back, which makes the links of the Twitter social network directed. |
|---------|--|

|       |  |
|-------|--|
| Weibo | <p>Sina Weibo (weibo.com) , often referred to as ‘Weibo’, is one of the biggest social media platforms of China. A short introduction to China’s most popular micro-blogging service. It was launched in August 2009. ‘Weibo’ literally means ‘micro-blog’; the prevalent form of social media in China today, comparable to ‘tweets’. There are multiple sites in China that offer micro-blogging services, but Sina Weibo is the most popular one around the Chinese web. By the end of 2012, it had over 400 million registered users (Chen et al 2012, 1); a significant majority of the 640 million Internet users that China holds. Weibo functions in a similar way as Twitter. There is a 140 character limit to each post and users are part of a “follower-followee network” (Gao et al 2012, 88). The relationship between followers and followees is unidirectional; one can ‘follow’ an individual and read their ‘tweets’ (referred to as ‘weibos’) without being followed back. Despite similar features, new research shows that there are quite some differences between how Weibo and Twitter is used. Not only do users of Sina Weibo publish more posts than those on Twitter, they also tend to disclose more personal information about themselves. They are more active in reacting on other people and sharing their views (Gao et al 2012, 93; Sullivan 2012, 774). While topics discussed on Twitter are often linked to institutions and companies, users of Sina avoid talking about (political) organizations or other institutions (Gao et al 2012, 96). The idea that Weibo is used in a more ‘personal’ way is supported by the fact that Sina Weibo users publish 19% more posts during the</p> |
|-------|--|

|  |  |
|--|--|
|  | weekends. This contrast to Twitter, where people post 11% less tweets on weekends than they do on weekdays (ibid. 2012, 98). |
|--|--|

Table 17 Data Sourcing: Twitter and Weibo (China's version of twitter)

### *Twitter*

A large dataset crawled through APIs from Twitter has been focused upon in this research.

Examples of twitter API:

|                         |   |
|-------------------------|---|
| <u>GET users/lookup</u> | Returns fully-hydrated user objects for up to 100 users per request, as specified by comma-separated values passed to the user_id and/or screen_name parameters. This method is especially useful when used in conjunction with collections of user IDs returned from GET friends/ids and GET followers/... |
| <u>GET users/show</u>   | Returns a variety of information about the user specified by the required user_id or screen_name parameter. The author's most recent Tweet will be returned inline when possible. GET users/lookup is used to retrieve a bulk collection of user  |

|                                |   |
|--------------------------------|---|
|                                | objects.  |
| <u>GET users/search</u>        | Provides a simple, relevance-based search interface to public user accounts on Twitter. Try querying by topical interest, full name, company name, location, or other criteria. Exact match searches are not supported. Only the first 1,000 matching results are available.                            |
| <u>GET users/contributees</u>  | Returns a collection of users that the specified user can "contribute" to.  |
| <u>GET users/contributors</u>  | Returns a collection of users who can contribute to the specified account.  |
| <u>POST mutes/users/create</u> | Mutes the user specified in the ID parameter for the authenticating user. Returns the muted user in the requested format when successful. Returns a string describing the failure condition when unsuccessful. Actions taken in this method are asynchronous and changes will be eventually consistent. |

Table 18 Examples of Twitter API

## *Weibo*

A large dataset crawled from Weibo has been focused upon in this research.

## *Examples of weibo's API*

### **User API**

users/show Return user profile by user ID (authorized user)

statuses/friends Return the user's following list and the latest weibo of each following user

statuses/followers Return the user's follower list and the latest weibo of each follower

users/hot Return system recommended users

user/friends/update\_remark Update remarks of authenticating user's following

users/suggestions Return the user that authenticating user may be interesting in

### **Friendships API**

friendships/create Follow a user

friendships/destroy Unfollow a user

friendships/exists Check if already follow a user (Recommend to use friendships/show instead)

friendships/show Return relationship of two users.

## **Social Graph API**

friends/ids Return user's following list

followers/ids Return user's follower list

### **3.3.4 EXPERIMENTAL DESIGN**

Researchers are concerned with the analysis of data generated from an experiment. It is wise to take time and effort to organize the experiment properly to ensure that the right type of data, and enough of it, is available to answer the questions of interest as clearly and efficiently as possible. This process is called experimental design (Easton & McColl, 1997). Because computer simulation is used to simulate WOM volume development over time, the experimental design is needed.

The design of an experiment should be influenced by (1) the objectives of the experiment, (2) the extent to which sequential experimentation will be performed, if at all, (3) the number of factors under investigation, (4) the possible presence of identifiable and non-identifiable extraneous factors, (5) the amount of money available for the experimentation, and (6) the purported model for modeling the response variable. Inman, Ledolter, Lenth, and Niemi (1992) stated, "Finally, it is impossible to



overemphasize the importance of using a statistical model that matches the experimental design that was actually used." If we turn that statement around, we should use a design that matches a tentative model, recognizing that we won't know the model exactly.

Following are a few desirable criteria for an experimental design:

- (1) The design points should exert equal influence on the determination of the regression coefficients and effect estimates, as is the case with almost all the designs discussed in this book.
- (2) The design should be able to detect the need for nonlinear terms.
- (3) The design should be robust to model misspecification
- (4) Designs in the early stage of the use of a sequential set of designs should be constructed with an eye toward providing appropriate information for follow up experiments

Box (1993) quoted R. A. Fisher: "The best time to design an experiment is after you have done it." Thus, experimentation should (ideally) be sequential, with subsequent experiments designed using knowledge gained from prior experiments, and budgets should be constructed with this in mind. Opinions do vary on how much of the budget should be spent on the first experiment. Daniel (1976) recommends using 50-67 percent of the resources on the first experiment, whereas Box, Hunter,

and Hunter (1978) more stringently recommend that at most 25 percent of the resources be used for the first experiment. Since sequential experimentation could easily involve more than two experiments, depending upon the overall objective(s), the latter seems preferable.

When we have two factors (i.e., variables) in an experimental design, we want to isolate the effect of each factor and also to determine if the interaction of the two factors is important. Here interaction simply means that the effect of a factor depends upon the level(s) of the other factor(s). The presence of interaction, particularly extreme interaction, can easily result in completely erroneous conclusions being drawn if an experimenter is not careful. Daniel (1976, p. 21) stresses that data from a designed experiment should not be reported in terms of main effects and interactions if an interaction is more than one-third of a main effect.

### *BASIC DESIGN CONCEPTS*

#### *Randomization*

Randomization is, loosely speaking, the random assignment of factor levels to experimental units. Ideally, the randomization method described by Atkinson and Bailey (2001) should be used whenever possible, although it is doubtful that hardly any experimenters actually

use it. Specifically, they state, "In a completely randomised design the treatments, with their given replications, are first assigned to the experimental units systematically, and then a permutation is chosen at random from the  $n!$  permutations of the experimental units (p. 57)." This is preferable to assigning the treatments (i.e., factor levels) at random to the experimental units, because a random assignment if performed sequentially will result, for example, in the last factor level being assigned to the last available experimental unit, which is clearly not a random assignment. The randomization method espoused by Atkinson and Bailey (2001) avoids these types of problems. Of course we could accomplish the same thing by, assuming  $t$  treatments, randomly selecting one of the  $t!$  orderings, and then randomly selecting one of the  $n!$  permutations of the experimental units and elementwise combining the juxtaposed lists.

Randomization is an important part of design of experiments because it reduces the chances of extraneous factors undermining the results, as illustrated in the preceding section. Czitrom (2003) stated, "The results of many semiconductor experiments have been compromised by lack of randomization in the assignment of the wafers in a lot (experimental units) to experimental conditions."

There are various detailed discussions of randomization in the literature, perhaps the best of which is Box (1990). The position taken by the author, which is entirely reasonable, is that randomization should be used if it only slightly complicates the experiment; it should not be used if it more than slightly complicates the experiment, but there is a strong belief that process stability has been achieved and is likely to continue during the experiment; and the experiment should not be run at all if the process is so unstable that the results would be unreliable without randomization but randomization is not practical.

Undoubtedly there are instances, although probably rare, when the use of randomization in the form of randomly ordering the runs can cause problems (e.g. John 2003)

### *Replication*

- E The distinction between replication and multiple readings is an important one, as values of the response variable  $Y$  that result from replication can be used to estimate, the variance of the error term for the model that is used. (Multiple readings, however, may lead to underestimation because the multiple readings might be misleadingly similar.) Values of  $Y$  that result from experiments that do not meet all the requirements of a replicated experiment may have variation due to

extraneous factor. One decision that must be made when an experiment is replicated is whether or not "replications" should be isolated as a factor. If replications are to extend over a period of time and the replicated observations can be expected to differ over time, then replications should be treated as a factor.

### *Blocking*

It is often said that an experimenter should randomize over factors that can be controlled and block factors that cannot be controlled.

## STEPS FOR THE DESIGN OF EXPERIMENTS

The specifics of procedures to follow will vary somewhat from setting to setting. Nevertheless, Bisgaard (1999) provided a template that is appropriate for factorial experiments that are to be used in a sequential manner. The starting point would be a statement of the reason for the experiment(s) and the objective(s). This should be followed by a list of the factors to be studied and the levels of each, a statement of the response variable(s) and how the measurements will be conducted.

Coleman and Montgomery (1993) also gave a thorough discussion of considerations that should be made in designing an experiment. They list

seven steps that should be performed sequentially: (1) recognition of and statement of the problem, (2) choice of factors and levels, (3) selection of the response variable(s), (4) choice of experimental design, (5) conduction of the experiment, (6) data analysis, and (7) conclusions and recommendations.

### *Recognition and Statement of the Problem*

Montgomery (1996) points out that the problem statement is often too broad. The problem should be specific enough and the conditions under which the experiment will be performed should be understood so that an appropriate design for the experiment can be selected.

### *Selection of Factors and Levels*

This issue has been addressed by Hahn (1977, 1984) and Cox (1958), in addition to Coleman and Montgomery (1993), with a more recent and more extensive discussion given by Czitrom (2003).

The factors that are studied in the initial stages of sequential experimentation are those that are believed to be important. The set can be reduced in later stages, so it is better to start with a large set than with

a small set that may not include some important factors. If an experimenter knew which factors were important, then the number of stages normally used in experimentation could be reduced, but such prior knowledge is generally unavailable. Sometimes a factor may not be recognized as important simply because its level isn't changed. Indeed, Myers and Montgomery (1995, p. 636) stated, "Often we have found that a variable was not realized to be important simply because it had never been changed."

### 3.3.5 COMPUTER SIMULATION EXPERIMENTS

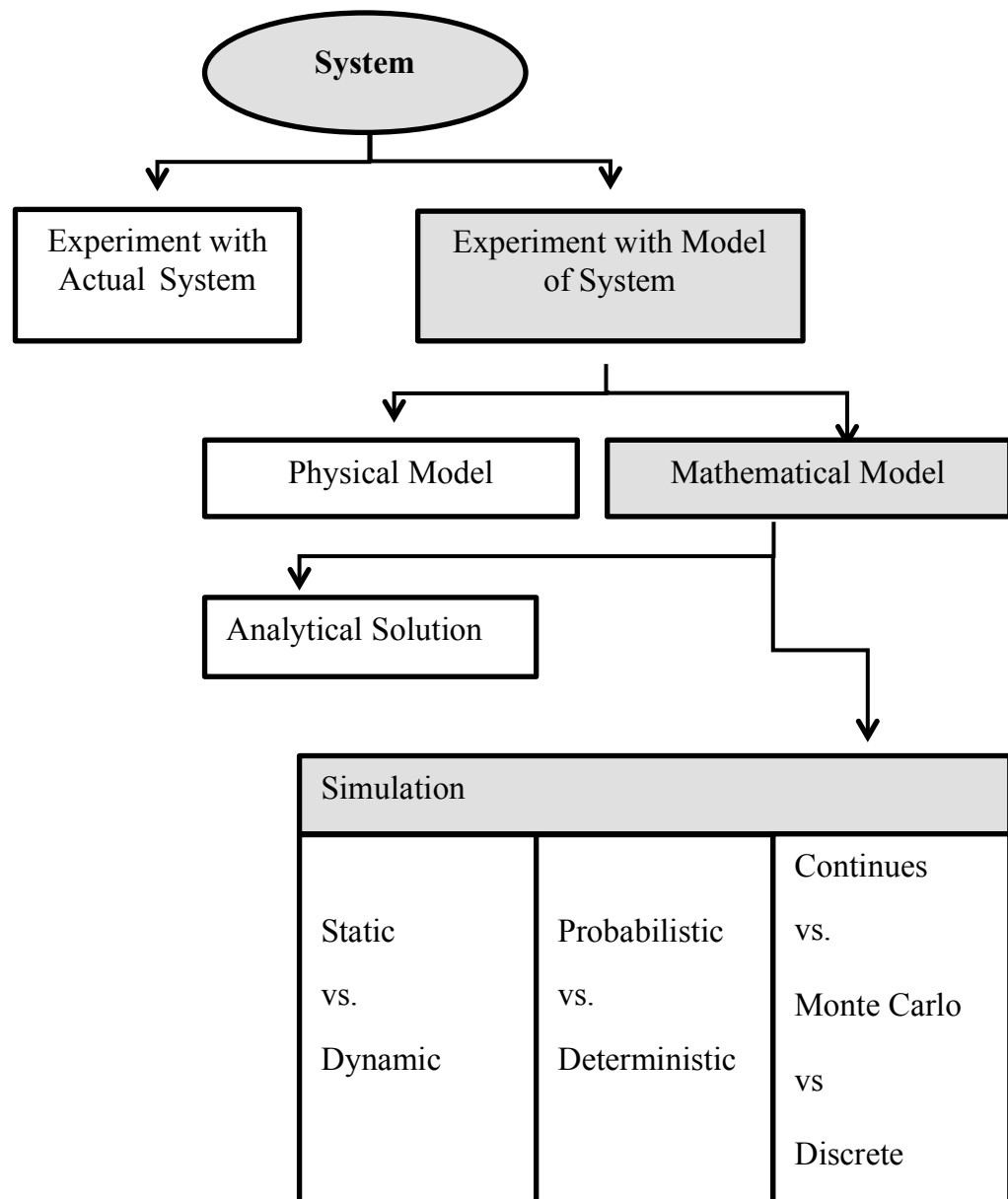


Figure 42 Computer Simulation Experiments

Figure 42 shows the relationship between computer simulation experiments and other sorts of experiments. Computer simulations,



although they are basically computations and do not involve any measurement interactions, nevertheless do generate new data about empirical systems, just as field experiments do, which means there is a distinctive relationship between the physicality of computer simulations (i.e. the fact that computer simulation are physical processes) and their being used as data generating experiments. Computer simulation experiments falls in the category of experiments with mathematical models of the system. Figure 43 shows the design flow of simulation experiment process.

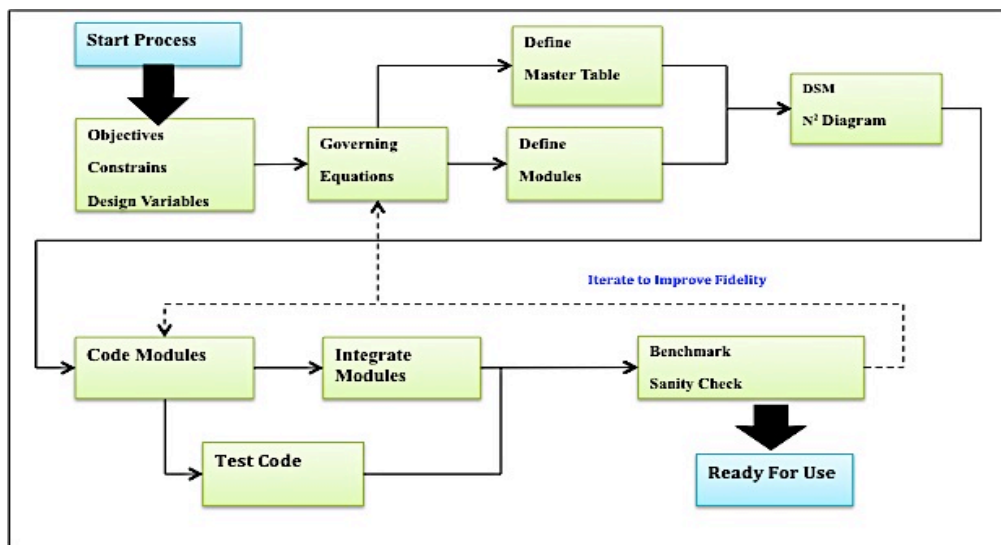


Figure 43 The Simulation Experiment Process

To explain figure 42 further, based on Law & Kelton (2000), a model is a mathematical object that has the ability to predict the behavior of a real system under a set of defined operating conditions and simplifying assumptions and simulation is the process of exercising a model for a

particular instantiation of the system and specific set of inputs in order to predict the system response.

According to the characteristics of mathematical models, they can be divided into deterministic models, probabilistic (stochastic) models, static models, dynamic models, continuous model, discrete model, linear models, nonlinear models and etc.

#### *Deterministic models*

Modeling in this manner researchers ignore random variation and try to formulate mathematical equations describing the basic fundamental relationships between the variables of the problem.

A mathematically deterministic model is a representation  $y = f(x)$  that allows you to make predictions of  $y$  based on  $x$ . Note that this "prediction" does not necessarily occur in the past, future, or even the present. It is simply a hypothetical, "what-if" statement. It helps us identify what would be the outcome if we were to use a particular  $x$ . For instance, in the population model we would aim to obtain an equation relating birth rates and death rates which themselves are related through equations to the population size at a

given time. In a sense we are constructing a model made of several empirical and interrelated sub-models, linking these sub-models together and then using the whole system to predict the outcome from a set of initial conditions.

This process is widely used and can be extremely accurate, such as in the case of predicting satellite orbits. It has the drawback that in other cases it is not possible to establish all the components mechanisms of a process or, even if this were possible, that including all known relationships render the model unwieldy.

This type of model is "deterministic" because  $y$  is completely determined if you know  $x$ . In real life, it is extremely rare that we can completely determine a  $y$  using an  $x$ , and thus we sometimes use stochastic (probabilistic) models. Actually, a deterministic model could be seen as a simplified stochastic model.

### *Stochastic models*

Another approach to modeling is the probabilistic or stochastic approach ('stochastic' comes from the Greek word to guess). Using this method we try to estimate the probability of certain outcomes based on the available

data. In terms of population example we would aim to establish a formula for the probability of a population changing size on the basis of assumed formulae for the probability of population births or deaths. These assumed formulae may in turn be based on probability distributions. Quantities of interest to be calculated would be standard statistics such as mean and the standard deviation of the population size.

A probability model is a representation  $Y \sim p(y)$ . This model also allows you to make "what-if" predictions as to the value of  $y$ , but, unlike the deterministic model, it does not allow you to say precisely what the value of  $y$  will be. In the case of WOM marketing, the model does not tell you precisely what the customer will do. However, the model does allow aggregate what-if predictions. Again, this "prediction" does not necessarily occur in the past, future, or even the present. It is simply a hypothetical, "what-if" statement. The probability model allows us to predict aggregate outcomes if we were to observe a large number of  $y$  values. These models can be extremely complicated although this is not necessarily the case. They do have the advantage of incorporating a degree of uncertainty within them. And ideally should be used when there is a high degree of variability in the problem. This method is typically used for models of small populations

when reproduction rates need to be predicted over a time interval. They also have valuable application in many other areas such as economic fluctuations, insurance problems, telecommunications and traffic theory and biological models.

System dynamics is a methodology for understanding change, using differential equations. System dynamics is grounded in the control theory and the modern theory of non-linear dynamics, and relies on the systems thinking and modeling for a complex world (Sterman, 2002). A systemic perspective enables one to make decisions consistent with the long-term best interests of the system as a whole (Sterman, 2001). According to Sterman (2001), dynamic complexity arises because systems have certain important characteristics:

- Systems are constantly changing.
- The actors (variables and constants) in a system interact strongly with one another and with the natural world, and everything is connected to everything else.
- Because of the tight link among the actors, our actions feedback on themselves. .
- Non-linear relationships exist, where the effect is rarely proportional

to cause.

- The system is history-dependent - past behavior influences future outcomes.
- The dynamics of system arise spontaneously from their internal structure. Often, small, random perturbations are amplified and molded by the feedback structure, generating patterns in space and time. There are self-organized critical states.
- The capabilities and behaviors of the actors in complex systems change over time.
- Time delays in feedback channels indicate the long-run response of a system to an intervention, often different from its short-run response.
- In complex systems, cause and effect are distanced in time and space, whereas we tend to look for causes near the events we seek to explain.

The physicality claim of computer simulations seems to underlie the metaphor of the computer a “a stand in for, or a probe of” the system upon which experiments are made, a metaphor used by Winsberg (2003) as well as Norton and Suppe (2001). This metaphor is central in Norton and Suppe’s paper. Since computer simulations allow one to vary initial and boundary conditions, as well as the values of control parameters, in the same way one can in real experiments, and even more so, the methodology of experimentation provides Norton and Suppe with a powerful argument in favor of this thesis (cf. Norton and Suppe, 2001,

56-57). In their attempt to explain why this is the case, Norton and Suppe resort to ontological properties of simulations. Simulations, according to them, “embed” theoretical models in real-world physical systems (computers). Therefore, even though computers used for simulations do not physically interact with their target systems, they can yield data in the same way field experiments do, namely by probing analogues of their target systems. The “embedding” of theoretical models acts as a reliable substitute for detection and measurement interactions.

R. I. G. Hughes (1999) presents a four-part comparison clarifying the notion of simulation. He first succinctly describes three non-computer simulations of physical processes, namely: a model water-wheel used to understand full-size water-wheels; the electrical model of a damped pendulum; and a cellular automaton, conceived as a physical system whose behavior can be the direct subject of experiment. He then contrasts these examples with a computer simulation of the atomic interactions between a pine and a plate described in Rohrlich (1991). According to him, in the first three examples, contrary to the computer simulation case, there is “an obvious correspondence between the process at work in the simulating device and those at work in the system being modeled”. “Nevertheless”, he adds, “like the systems examined

[the first three simulating systems], the computer is a material system, and in using it to provide answers to our questions we are relying on the physical processes at work within it.” (p. 139, our emphasis) Here again, physicality seems to be a crucial feature but Hughes provides us with no further details about his own interpretation of the physicality claim.

Finally, Humphreys (1994) argues that when a program runs on a digital computer, the resulting apparatus is a physical system, i.e., any runs of the algorithm are just trials on a physical system. This is a new version of the physicality claim. Humphreys further points out that “there is no empirical content to these simulations in the sense that none of the inputs come from measurements or observations. ... It is the fact that they have a dynamical content due to being implemented on a real computer device that sets these models apart from ordinary mathematical models” (1994, p. 112).

The notion of a “dynamical content” is not a standard one and is thus difficult to understand. Even if allusions to the “essentially dynamic nature of simulations” are common-place (as shown in the “Research questions” presenting the “Models and Simulations” Workshop held in June 2006 in Paris), this “dynamic nature” is left unanalyzed. However, it is undoubtedly connected with the fact that computer simulations are,



at a basic level, physical processes occurring on concrete devices (cf. also Hartmann 1996). Since they are sequences of physical events, namely physical state transitions, they are particular processes, localized in space and time, exactly as field experiments are. Moreover, the cognitive importance of the fact that, during the performing of (at least some) simulations, something happens before our eyes on the computer's screen so that we can see the evolution of the model we have "put in" the computer, cannot be overestimated in any epistemological description of how we explore computational models. However, Humphreys' claim that "there is no empirical content in these computer simulations" is apparently at odds with the fact that, whereas simulations do not involve measurement interactions, some of them nevertheless contribute like field experiments to providing knowledge about physical systems.

The term "data" is commonly used in two senses that are conflated when it is applied to field experiments, but need to be distinguished when applied to simulations. Data may be:

- of empirical origin, namely produced by physical interactions with measuring or detecting devices,
- and/or about a physical system.

### General features of computer simulations

Any general analysis of computer simulations must clearly distinguish between:

(a) an incomplete program that includes every single algorithm that is actually used. To be completed, this program only requires that someone enter the values of the relevant variables;

(b) a completed program that only requires someone to press the “run” key to run. This program includes various operations such as the writing of data in a folder, test operations, opening of visual interfaces for visualization. These operations do not have any representational role.

The completed program in turn gives way to:

(c) the running completed program, a process corresponding to the exact running of (b);

(d) the data resulting from (c). These are the data written in the files, i.e. the numbers that can be interpreted as raw data about the represented systems; and finally,

(e) the computer-made analysis of the vast amounts of data (d).

### *Computer Simulations: The Simulation of WOM Volume Development*

## THE WOM VOLUME MODELS

### *WOM Volume Development*

Consider  $N$  agents (individuals in a social network) existing on an undirected graph  $G(S, \Gamma)$ , where  $S = \{1, \dots, N\}$  is a finite set of nodes (agents) and  $\Gamma = \{\Gamma_i, i \in S\}$  is the list of connections. Specially,  $\Gamma_i = \{j \in S - \{i\} | d(i, j) = 1\}$ , where  $d(i, j)$  is the length of the shortest path from node  $i$  to node  $j$  on the graph. Each agent  $i \in S$  is characterized by a WOM volume number which increase as the agent's broadcast posts get forwarded by other agents.

Formally, let

### *WOM Volume development in complex networks*

The simulation of WOM volume development is run on the four

representative network models: tree networks (branching process), random network, small-world network and scale-free network.

Random network: According to the Erdős and Rényi model, this research start with  $N$  nodes and connect every pair of nodes with probability  $p$ ,

creating a graph with approximately  $\frac{pN(N-1)}{2}$  edges distributed randomly. In order to keep the average degree the same with the other three

networks, the author chooses  $p = \frac{2z}{(N-1)}$ , and only the connected networks are considered.

Small-world network: The algorithm of the WS model is the following:

(1) start with a ring lattice with  $N$  nodes in which every node is connected to its first  $2z$  neighbors. In order to have a sparse but connected network at all times, consider  $N \gg 2z \gg \ln(N) \gg 1$

(2) Randomly rewire each edge of the lattice with probability  $P$  such that self-connections and duplicate edges are excluded. This process introduces  $PNz$  long-range edges.

The algorithm of the SF model is the following:

1. Growth: Starting with a small number ( $m$ ) of nodes, at every timestep

we add a new node with  $z(<m)$  edges that link the new node to  $m$  different nodes already present in the system.

2. Preferential attachment: When choosing the nodes to which the new node connects, we assume that the probability  $\Pi$  that a new node will be connected to node  $i$  depends on the degree  $k_i$  of node  $i$ , such that

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j}$$

After  $t$  time steps this procedure results in a scale-free network with  $N = t + m$  nodes and  $zt$  edges, whose average degree is approximately  $2z$ .

### *Estimating the Model Parameters*

The strength of the network topology models is that their parameters can be estimated using the individual-level data obtained from social networks as described in the web crawling section.

Hence, in contrast to most models in marketing, this research does not estimate the model parameters using the functional form as represented by equations and data on the actual process variables. Instead, this research use the dynamically generated database containing the individual-level data of

the process from which I infer the model parameters. The estimates based on these individual-level data are subsequently inserted into the model to predict the number of participants over time. This approach is similar to pretest market models (Hauser and Wisniewski 1982, Shocker and Hall 1986), including Sprinter (Urban, 1970), Perceptor (Urban 1975), ASSESSOR (Silk and Urban 1978), Tracker (Blattberg and Golanty 1978), and MOVIEMOD (Eliashberg et al. 2000) that predict market shares or diffusion curves based on customers' trial and adoption processes. For these models, the process parameters are estimated before the start of the diffusion process using data from surveys and experiments. For my topology WOM volume models, I estimate the parameter values directly from the individual-level data that become available from the viral process of interest through web crawling and that are stored in a dynamic database. The model parameters can be quickly estimated reliably because this database contains many customers already in the viral campaign's early stages.

Table 26 summarized the variables for the modeling of online WOM volume.

|                       |  |
|-----------------------|--|
| $t \in [0, \dots, T]$ | Denote continuous time, with $t=0$ as the start and $t=T$ the end of the EWOM volume development process |
|-----------------------|--|

|                  |   |
|------------------|---|
| $Y(t)$           | Denote the cumulative number of EWOM volume on a social website in the EWOM volume development process at time $t$  |
| $U(t)$           | Denote the number of social network site users who retweet / reblog the SEEDING tweet/weibo after the seeding post be presented on that user's social networking site page. |
| $W(t)$           | Denote the number of social network site users who retweet / reblog the VIRAL tweet/weibo yet after the viral post be presented on that user's social networking site page. |
| $G(t)$           | Denote the vector $[U(t), W(t), Y(t)]$  |
| $s$              | Denote all the retweeting and reblogging sources.<br><br>i.e. $s \in \{seeding \text{ posts}, viral \text{ posts}\}$  |
| $\beta$          | Denote the average number of retweets/reblogs a participant gets.   |
| $\varphi_{12}^s$ | Denote the probability of retweeting/reblogging upon seeing the tweet/weibo posted by source $s$  |
| $1/\gamma_u$     | Denote the average time between a seeding post be posted and be retweeted/reblogged   |
| $1/\gamma_w$     | Denote the average time between a viral post be posted  |

|  |                            |
|--|----------------------------|
|  | and be retweeted/reblogged |
|--|----------------------------|

Table 26 variables for the modeling of online WOM volume.

Figure 44 and Figure 45 shows the dynamics of the EWOM volume development in twitter and weibo from a participant's perspective.

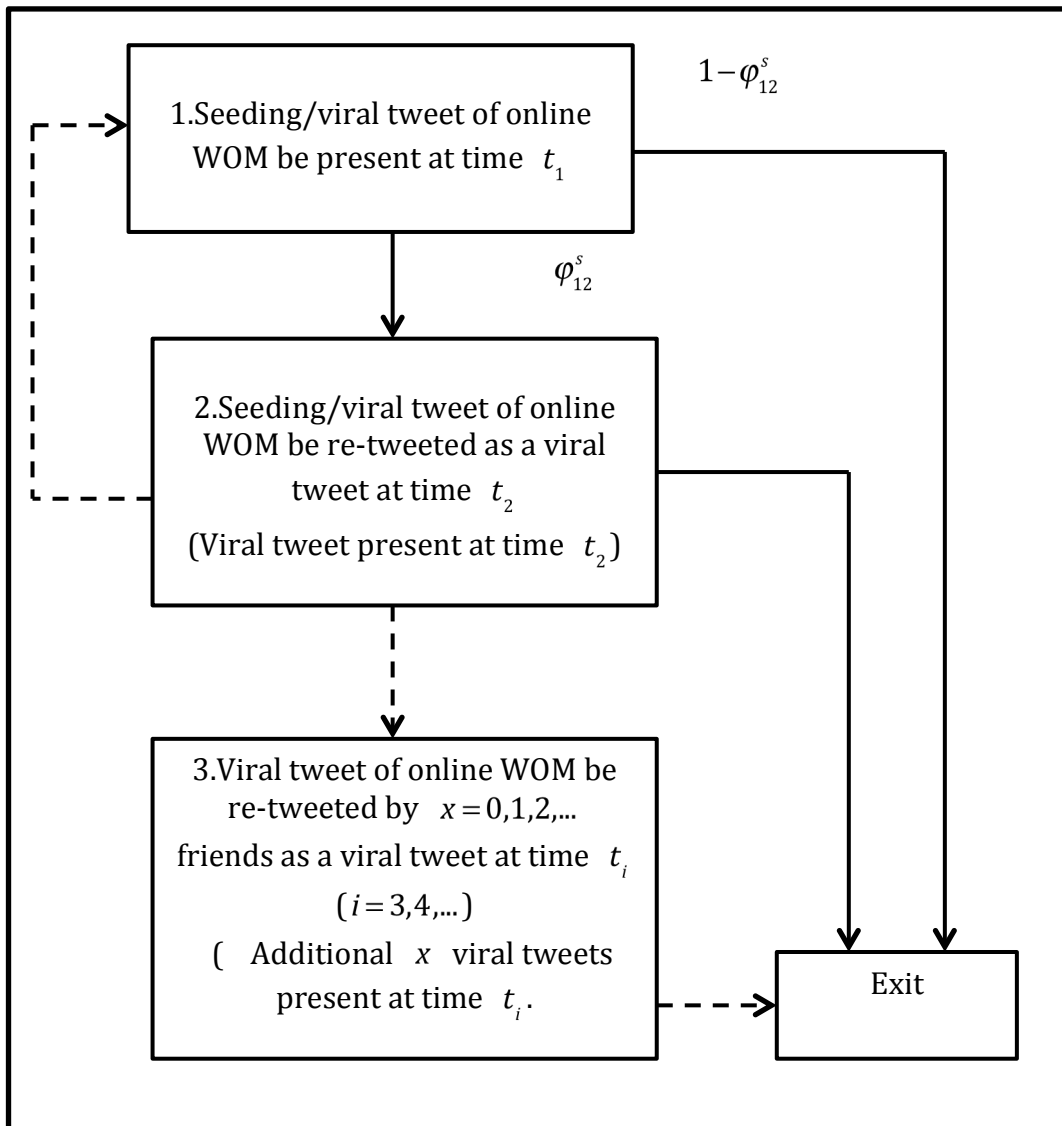


Figure 44 An EWOM Volume Development Process from a Participant's Perspective (Twitter)

(Note: Here  $\varphi_{12}^s$  represents the probability of the tweet getting re-tweeted



and reaches stage 2.  $1-\varphi_{12}^s$  represents the probability of the tweet exiting the WOM volume development process.)

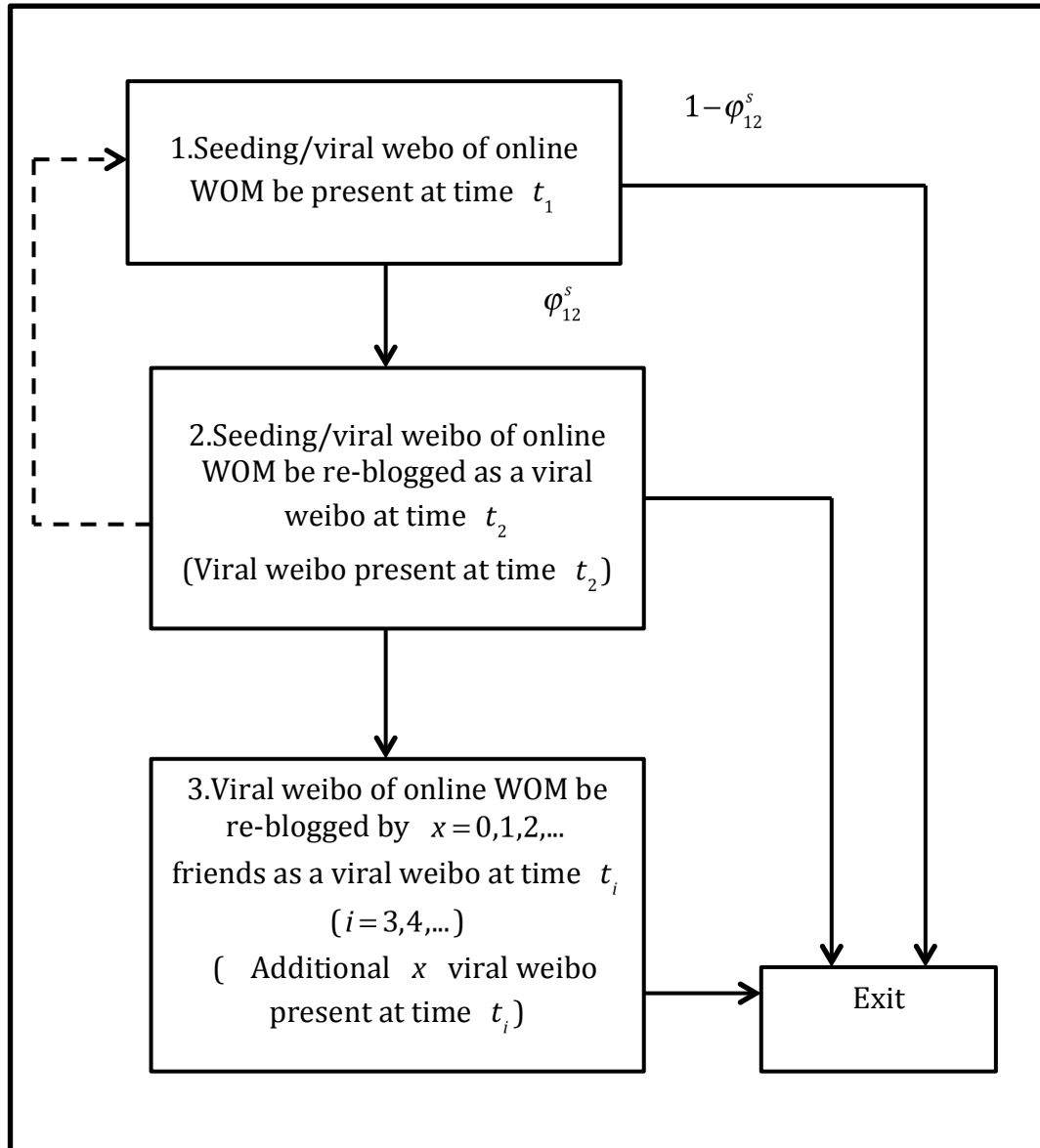


Figure 45 An EWOM Volume Development Process from a Participant's Perspective (Weibo)

(Note: Here  $\varphi_{12}^s$  represents the probability of the weibo getting reposted.

$1-\varphi_{12}^s$  represents the probability of the weibo exiting the EWOM volume

development process.)

Figure 46 explains how the process in Figure 44 and Figure 45 works.

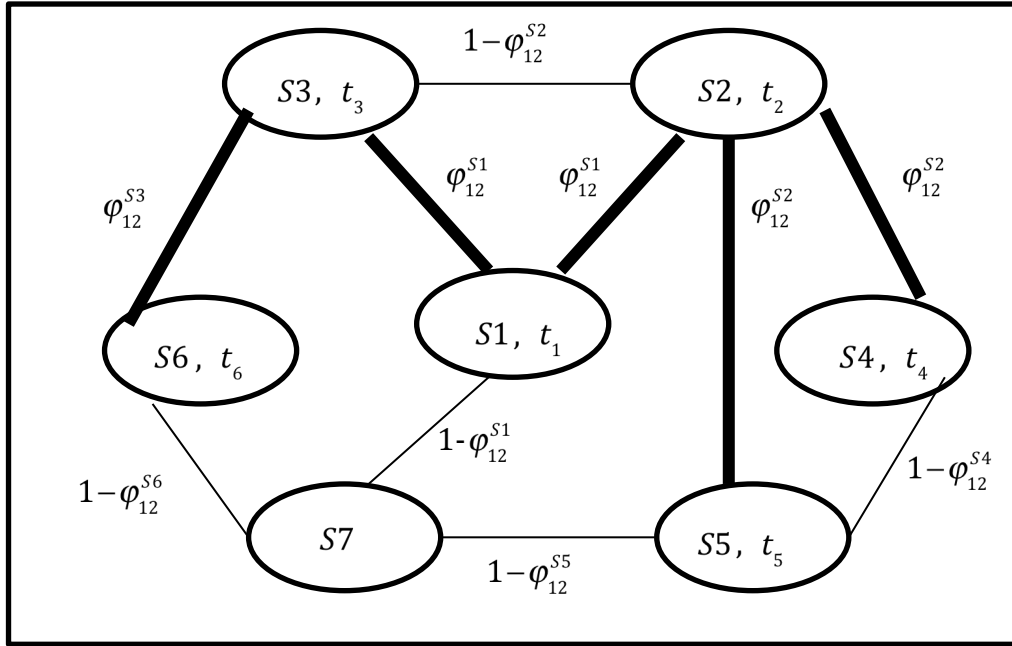


Figure 46 An Example of EWOM Volume Development Process in a Complex Network Illustrating Some of the Variables

(Note:  $\phi_{12}^{S1}$  represents the probability of S1 getting reposted.  $1 - \phi_{12}^{S1}$  represents the probability of S1 exiting the EWOM volume development process;  $\phi_{12}^{S2}$  is the probability of S2 getting reposted, and  $1 - \phi_{12}^{S2}$  refers to the probability S2 exiting the EWOM volume development process, and so on.)

Corresponding to the variables, Figure 45, Figure 46 and Figure 47, Table 27 illustrates an example of realization of the complex network topology

model with one seeding source S1. At time  $t_1$ , source S1 posted a seeding post and therefore  $Y(t)$  equals 1 with no retweets/reblogs yet (i.e. both  $U(t)$  and  $W(t)$  equal 0). At time  $t_2$ , S2 retweets/reblogs after reading the post (i.e.  $U(t)=1$ ), there are 2 cumulative posts online so far ( $Y(t)=2$ ), and because S2 has no viral retweets/reblogs yet,  $W(t)=0$ . At time  $t_3$ , S3 retweet/reblogs from source S1 (i.e.  $Y(t) +1$ ), as S1 is a seeding post,  $W(t)$  stays 0,  $U(t)$  adds 1. At time  $t_4$ , S4 retweets/reblogs from source S2 (i.e.  $Y(t)+1$ ), and as it is a viral tweet,  $W(t)$  adds 1 (i.e.  $W(t)=1$ ). At time  $t_5$ , S5 retweets/reblogs from viral source S2 (i.e.  $Y(t)+1$ ,  $W(t)+1$ ). At time  $t_6$ , S6 retweets/reblogs from viral source S3 (i.e.  $Y(t)+1$ ,  $W(t)+1$ ),  $U(t)$  do not change.

|        | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_5$ | $t_6$ |
|--------|-------|-------|-------|-------|-------|-------|
| $Y(t)$ | 1     | 2     | 3     | 4     | 5     | 6     |
| $U(t)$ | 0     | 1     | 2     | 2     | 2     | 2     |
| $W(t)$ | 0     | 0     | 0     | 1     | 2     | 3     |

Table 19 An Example of Realization of the Complex Network Topology  
Model with One Seeding Source

The EWOM volume development process is a continuous-time Markov process. Therefore  $G(t) = [U(t), W(t), Y(t)]$  is a three-dimensional continuous-time Markov process. Differential equations play a crucial role in determining the values of the interrelated state variables  $G(t)$  over time in a continuous-time Markov process.

The predicted number of social network site users who retweet / reblog the SEEDING tweet/weibo after the seeding post be presented on that user's social networking site page.

$$f(U(t)|U(t')=i_u) = i_u e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')}$$

The predicted number of social network site users who retweet / reblog the SEEDING tweet/weibo after the seeding post be presented on that user's social networking site page.

$$f(W(t)|W(t')=i_w) = i_w e^{\gamma_w (\varphi_w^x - 1)(t-t')} \\ \frac{\gamma_w \varphi_w^x i_w}{\gamma_w (\varphi_w^x - 1) + \gamma_u} \left( e^{\gamma_w (\varphi_w^x - 1)(t-t')} - e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')} \right) +$$

The predicted cumulative number of EWOM volume on a social website in the EWOM volume development process at time  $t$

$$f(Y(t)|Y(t')=i_y) = i_y e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')} \\ + i_w e^{\gamma_w (\varphi_w^x - 1)(t-t')} + \frac{\gamma_w \varphi_w^x i_w}{\gamma_w (\varphi_w^x - 1) + \gamma_u} \left( e^{\gamma_w (\varphi_w^x - 1)(t-t')} - e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')} \right) + 1$$

### *Artificial Neural Network in Matlab*

The main advantage of neural networks is that it is possible to train a neural network to perform a particular function by adjusting the values of connections (weights) between elements. Artificial neural networks (ANN) have memory. The memory in neural networks corresponds to the weights in the neurons. Neural networks can be trained offline and then transferred into a process where adaptive learning takes place. In our case, a neural network controller could be trained to predict the WOM valence value in the simulink environment. After training with real data set crawled from social website, the network weights are set. The ANN is placed in a feedback loop with the actual WOM valence decision process. The network will also adapt the weights to improve performance as it apply to social network WOM valence prediction in the future. The process is illustrated in the flow chart below (Figure 37).

The main disadvantage of ANN is they operate as black boxes. The rules of operation in neural networks are completely unknown. It is not possible to convert the neural structure into known model structures.

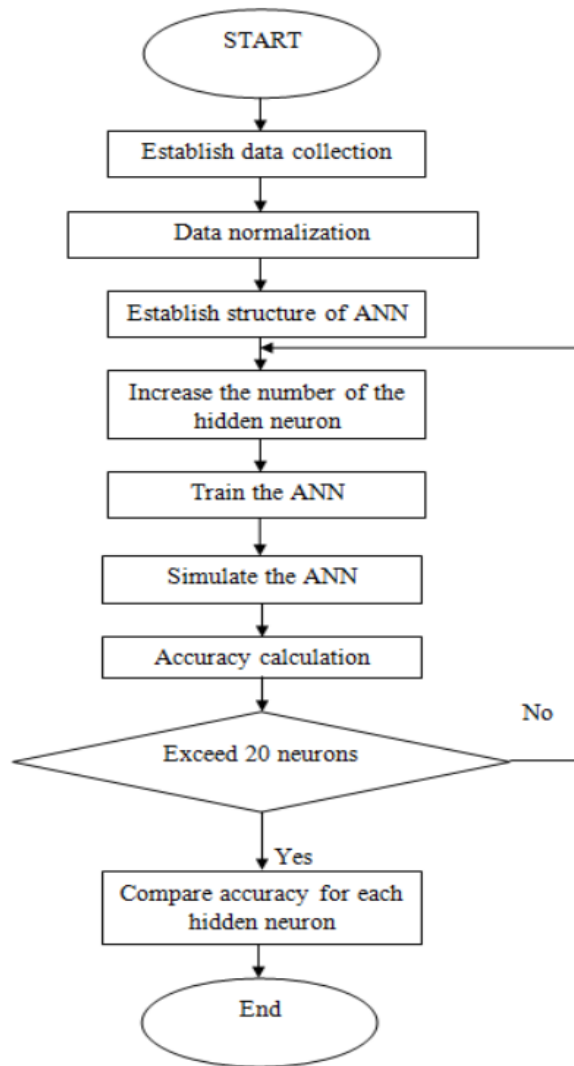


Figure 48 Process of ANN modeling

As discussed and displayed in chapter 2, the input variables of ANN model are

|       |                 |
|-------|-----------------|
| $I_1$ | Satisfaction    |
| $I_2$ | Loyalty         |
| $I_3$ | Quality         |
| $I_4$ | Commitment      |
| $I_5$ | Trust           |
| $I_6$ | Perceived Value |

NVivo software was used to code the inputs data from twitter and weibo as the inputs nodes (Figure 47 and Figure 48). An introduction of NVivo is in the appendix.

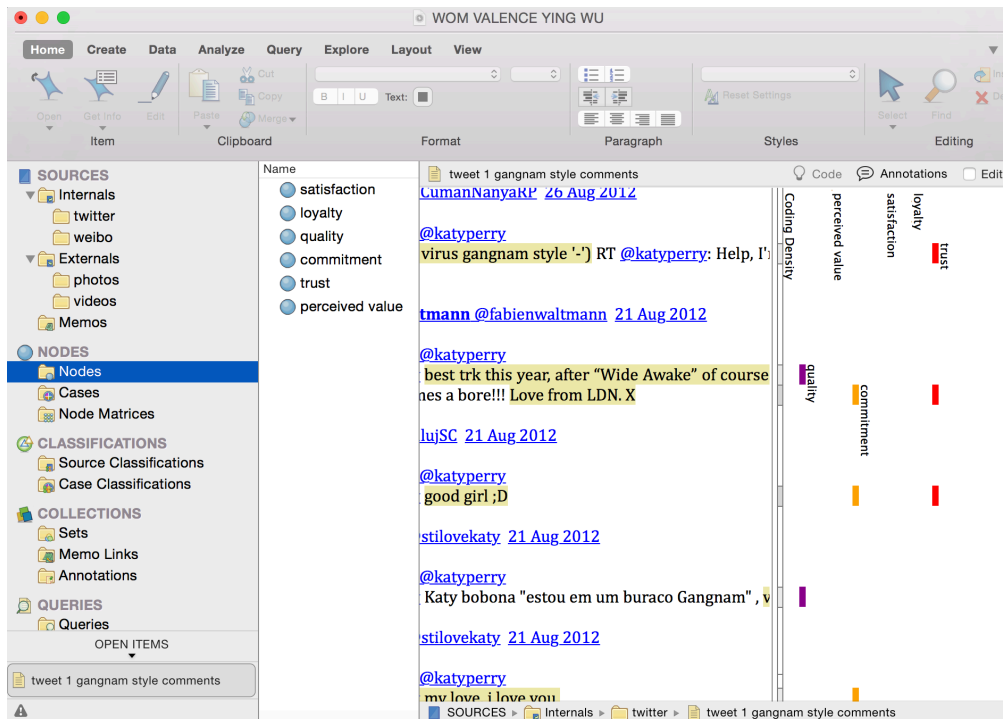


Figure 47 NVivo Screenshot of Coding the Input Nodes of the ANN Model (Twitter)

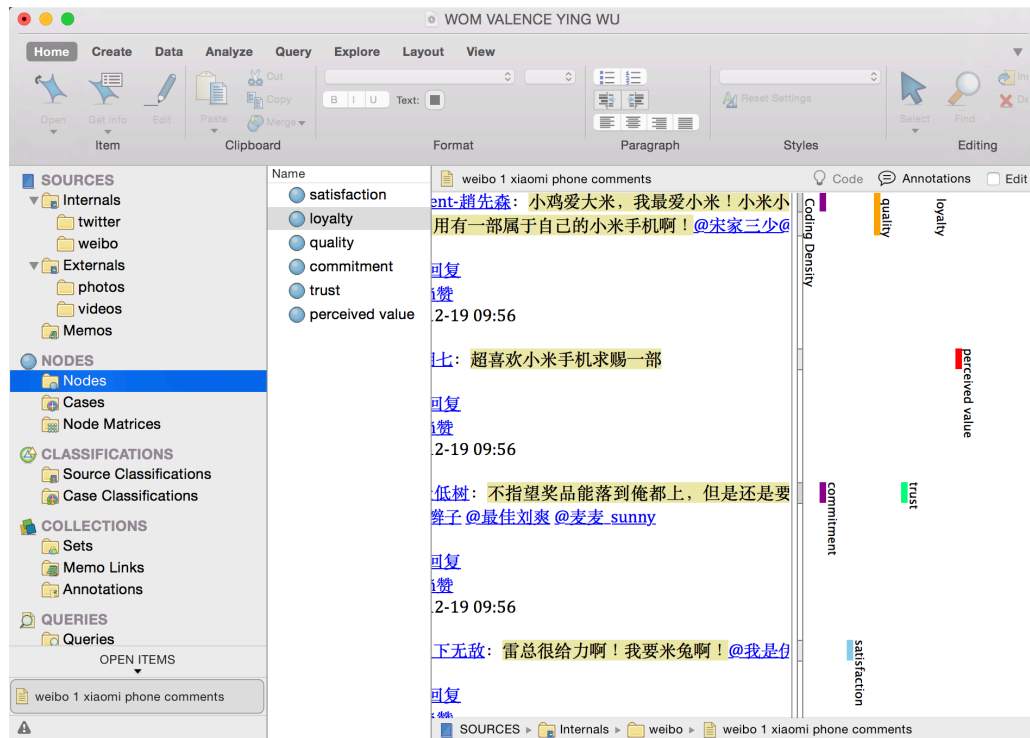


Figure 48 NVivo Screenshot of Coding the Input Nodes of the ANN Model (Weibo)

Back propagation network uses gradient-descent based delta learning rule, also known as back propagation rule thereby minimises the total squared error of the output computed by the network. It provides a computationally efficient method for changing the weights in the network with differentiable activation function units to learn a set of input output patterns. It aims to achieve the balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good responses to the input patterns that are similar. Figure 23 illustrated the back propagation network.

In the training phase, the weights, biases and the learning rate  $\alpha$  are



initialised to small random values. Activations for the training input units and target output units are set. The net inputs to the neurons present in the hidden layer are calculated. The output of the hidden unit is calculated by applying the binary sigmoidal activation function. Activations for the hidden units are set. The net inputs to the neurons present in the output layer are calculated. The output of the output unit is calculated by applying the binary sigmoidal function. The error correction term due to the error at hidden units are computed based on which the changes in weights and biases are done to the input layer backwards. The network is trained till certain number of epochs reached or till the calculated output equals the target output.

### ***Training Algorithm for the Modeling of WOM valence***

#### **Phase 1 – Initialization of weights**

Step 1: Initialize the weights, biases and learning rate to small random values.

Step 2: Perform steps 3-10 when stopping condition is false.

Step 3: Perform steps 4-9 for each training pair.

#### **Phase 2 – Feed forward phase**

Step 4: Each input unit receives input signal  $I_m$  ( $m=1$  to 6). And sends it to the hidden unit.

Step 5: Each hidden unit  $H_n$  ( $n= 1$  to  $p$ ) sums its weighted input signals to

calculate net input

$$Hin_n = v_{0n} + \sum_{m=1}^{m=6} I_m v_{mn}$$

Calculate the output of the hidden unit by applying its binary sigmoidal  
activation function over  $Hin_n$

$$H_n = f(Hin_n) = \frac{1}{1 + e^{-Hin_n}}$$

and send the output signal from the hidden unit to the input of the output  
layer units.

Step 6: For each output unit  $y$ , calculate the net input

$$yin = w_0 + \sum_{n=1}^{n=6} z_n w_n$$

and its binary sigmoidal activation function is applied to compute the output  
signal.

$$y = f(yin) = \frac{1}{1 + e^{-yin}}$$

### **Phase 3 – Back propagation of error**

Step 7: Output unit  $y$  receives a target pattern corresponding to the input  
training pattern and computes the error correction term.

$$\delta = (t - y) f'(yin)$$

On the basis of the calculated error correction term update the change in  
weights and bias

$$\Delta w_n = \alpha \delta H_n$$

$$\Delta w_0 = \alpha \delta$$

Also send  $\delta$  to the hidden layer backwards.

Step 8: Each hidden unit sums its delta inputs from the output units.

$$\delta_{inn} = \delta w_n$$

The term  $\delta_{inn}$  gets multiplied with the derivative of  $f(H_{inn})$  to calculate the error term

$$\delta_n = \delta_{inn} f'(H_{inn})$$

On the basis of  $\delta_n$  update the change in weights and bias

$$\Delta v_{mn} = \alpha \delta_n I_m$$

$$\Delta v_{on} = \alpha \delta_n$$

#### Phase 4 – Weights and bias update

Step 9: Output unit updates the bias and weights

$$w_n(new) = w_n(old) + \Delta w_n$$

$$w_0(new) = w_0(old) + \Delta w_0$$

Each hidden unit updates its bias and weights

$$v_{mn}(new) = v_{mn}(old) + \Delta v_{mn}$$

$$v_{on}(new) = v_{on}(old) + \Delta v_{on}$$

Step 10: Check for the stopping condition. The stopping condition be the certain number of epochs.

In the testing phase, the net inputs to the hidden layer neurons are calculated taking weights from the training phase after setting the activations of the input units. The output of the hidden unit is calculated by applying the binary sigmoidal activation function. Activations for the hidden units are set. The net inputs to the neurons present in the output layer are calculated. The output of the output unit is calculated by applying the binary sigmoidal function. If all the calculated output units are equal to the target output units then the response is considered as positive; else the response is considered as negative.

### ***Testing Algorithm for the modeling of WOM valence***

#### **Phase 1 – Initialization of weights**

Step 1: Weights and bias to be used are taken from the training algorithm.

Step 2: Perform steps 3-6 for each input vector.

#### **Phase 2: Feed forward phase**

Step 3: Set the activation of input unit  $I_m$  (m=1 to 6).

Step 4: Calculate the net input to the hidden unit  $H$  and its output for n=1 to p.

$$Hin_n = v_{0n} + \sum_{m=1}^{m=6} I_m v_{mn}$$

$$H_n = f(Hin_n) = \frac{1}{1 + e^{-Hin_n}}$$

Step 5: Compute the output of the output layer unit

$$yin = w_0 + \sum_{n=1}^p H_n w_n$$

$$y = f(yin) = \frac{1}{1 + e^{-yin}}$$

Binary sigmoidal activation function is used for calculating the output.

Step 6: Calculate the response

If  $y = t$

Reponse is positive

Else

Response is negative

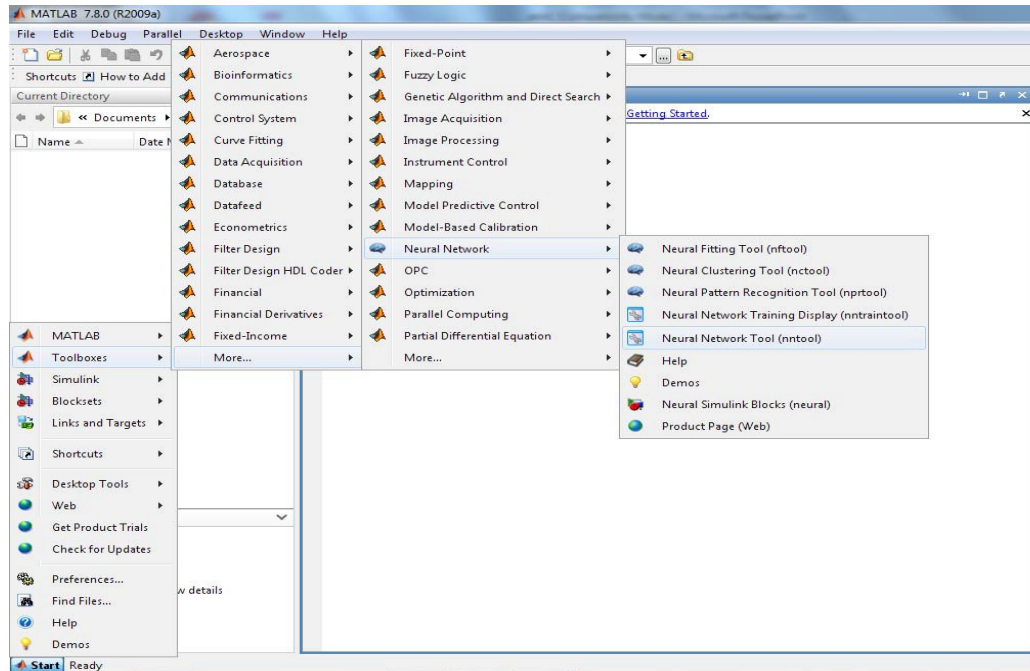


Figure 49 ANN Modeling Platform MATLAB

### 3.4 CHAPTER SUMMARY

This chapter has been divided into two sections. The first section deals with the philosophical positioning and the second with the research methodology and design adopted. The next Chapter deals with the analysis of the findings.

## CHAPTER FOUR

### DATA ANALYSIS AND DISCUSSION

#### 4.1 DATA ANALYSIS AND DISCUSSION OF WOM VOLUME

The gangnam style tweet (figure 50) and the xiaomi phone weibo (figure 51) were used to develop the network topology model and run the computer simulation experiments.



Figure 50 One Twitter Post Used for Web Crawling On Twitter

This Gangnam Style tweet was posted on 21st Aug 2012 while the song "Gangnam Style" was released on July 15, 2012 by the South Korean musician Psy. The phrase "Gangnam Style" is a Korean neologism and it refers to a lifestyle that is associated with the Gangnam District of Seoul. The music video of this song went viral in August 2012 after being tweeted by celebrities such as Katy Perry on twitter and has influenced popular culture worldwide since then. This tweet from Katy Perry was one of the most significant triggers that started the viral spread of the video. Moreover, Guinness World Records recognized "Gangnam Style" as the most "liked" video on YouTube in September 2012 (Guinness world records, 2012). By the end of 2012, the song had topped the music charts of more than 30 countries including Australia, Canada, France, Germany, Italy, Russia, Spain, and the United Kingdom (Cochrane, 2012). Therefore this tweet shown in Figure 41 was selected to crawl data from and the collected data of the tweet from web crawling has been used as the benchmark for assessing the performance of the model.

Table 20 A Network Topology Overview of Katy Perry's Tweet

|                               |   |
|-------------------------------|---|
| <b>Web Crawling Time span</b> | 21 <sup>th</sup> August 2012–<br>21 <sup>th</sup> December 2012 |
| <b>#nodes</b>                 | 11,207  |
| <b>#edges</b>                 | 2,430,206   |



【#小米手机2微博开卖# 转发狂送20台】新浪微博社会化网购首单，12月21日中午12点，5万台#小米手机2#微博专场销售。全球首款28nm四核手机，2G大内存，新一代背照式相机，1999元性价比之王。现在起至20日，关注@小米手机，转发@好友，每天10点-20点每2小时送出2台米2。微博预约 [网页链接](#)



Figure 51 One Weibo post used for web crawling

Note: This tweet is in Chinese - [#I phone 2 started selling on Weibo # forward this tweet and you will win a chance to get a XIAOMI phone 2 for free. There will be 20 of you wining our brand new phones] The first special purchase link towards the special sale on Weibo platform is published here in Sina Weibo social network . At 12:00 on December 21, we have 50000 phones to be sold to you exclusively on Weibo platform # XIAOMI phone 2 # The world's first 28nm quad-core phone , 2G memory , a new generation of back-illuminated camera , King of value-for-money:only1999RMB . From now untill the 20<sup>th</sup>, follow @ XIAOMI phone , forward and @ friends to join the prize draw, every day from 10.00 AM to 2.00 PM we send two of you free XIAOMI phone 2 . Weibo reservation link:

(This tweet had been forwarded 2,593,195 times in two days. Gangnam

Style posts have not been selected because none of the posts promoting the original Gangnam style song went viral on Weibo )

Table 21 A Network Topology Overview of XIAOMI Weibo Volume

Development

|  |   |
|--|---|
| <b>Time span of tweets<br/>posting times</b> | 19 <sup>th</sup> December<br>2012–19 <sup>st</sup> February<br>2013 |
| <b>#nodes</b>                                | 1,291,352   |
| <b>#edges</b>                                | 154,970,488   |

This thesis sets out to understand the dynamics of WOM volume and the modeling approach using network topologies. Therefore rounds of random, scale-free, small-world and tree (branching) network topologies were simulated.

The strength of the network topology models is that their parameters can be estimated using the individual-level data obtained from social networks as described in the web crawling section.

Hence, in contrast to most models in marketing, this research does not estimate the model parameters using the functional form as represented by equations and data on the actual process variables. Instead, this research

used the dynamically generated database containing the individual-level data of the process from which I infer the model parameters. The estimates based on these individual-level data are subsequently inserted into the model to predict the number of participants over time. This approach is similar to pretest market models (Hauser and Wisniewski 1982, Shocker and Hall 1986), including Sprinter (Urban, 1970), Perceptor (Urban 1975), ASSESSOR (Silk and Urban 1978), Tracker (Blattberg and Golanty 1978), and MOVIEMOD (Eliashberg et al. 2000) that predict market shares or diffusion curves based on customers' trial and adoption processes. For these models, the process parameters are estimated before the start of the diffusion process using data from surveys and experiments. For my topology WOM volume models, I estimate the parameter values directly from the individual-level data that become available from the viral process of interest through web crawling and that are stored in a dynamic database. The model parameters can be quickly estimated reliably because this database contains many customers already in the viral campaign's early stages.

The variables are illustrated in the table 29.

|                       |   |
|-----------------------|---|
| $t \in [0, \dots, T]$ | Denote continuous time, with $t=0$ as the start and $t=T$ the end of the EWOM volume development process  |
| $Y(t)$                | Denote the cumulative number of EWOM volume on a social website in the EWOM volume development process at time $t$  |
| $U(t)$                | Denote the number of social network site users who retweet / reblog the SEEDING tweet/weibo after the seeding post be presented on that user's social networking site page. |
| $W(t)$                | Denote the number of social network site users who retweet / reblog the VIRAL tweet/weibo yet after the viral post be presented on that user's social networking site page. |
| $G(t)$                | Denote the vector $[U(t), W(t), Y(t)]$  |
| $s$                   | Denote all the retweeting and reblogging sources.<br><br>i.e. $s \in \{\text{seeding posts, viral posts}\}$   |
| $\beta$               | Denote the average number of retweets/reblogs a participant gets.   |
| $\varphi_{12}^s$      | Denote the probability of retweeting/reblogging upon  |

|              |   |
|--------------|---|
|              | seeing the tweet/weibo posted by source $s$   |
| $1/\gamma_u$ | Denote the average time between a seeding post be posted and be retweeted/reblogged |
| $1/\gamma_w$ | Denote the average time between a viral post be posted and be retweeted/reblogged   |

Table 22 Variables for the Modeling of Online WOM Volume.

The EWOM volume development process is a continuous-time Markov process. Therefore  $G(t) = [U(t), W(t), Y(t)]$  is a three-dimensional continuous-time Markov process. Differential equations play a crucial role in determining the values of the interrelated state variables  $G(t)$  over time in a continuous-time Markov process.

The predicted number of social network site users who retweet / reblog the SEEDING tweet/weibo after the seeding post be presented on that user's social networking site page.

$$f(U(t)|U(t')=i_u)=i_u e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')}$$

The predicted number of social network site users who retweet / reblog the SEEDING tweet/weibo after the seeding post be presented on that user's social networking site page.

$$f(W(t)|W(t')=i_w)=i_w e^{\gamma_w (\varphi_w x - 1) (t-t')}$$

$$\frac{\gamma_w \phi_w x_i}{\gamma_w (\phi_w x - 1) + \gamma_u} \left( e^{\gamma_w (\phi_w x - 1)(t-t')} - e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')} \right) +$$

The predicted cumulative number of EWOM volume on a social website in  
the EWOM volume development process at time  $t$

$$f(Y(t)|Y(t')=i_y) = i_u e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')} \\ + i_w e^{\gamma_w (\phi_w x - 1)(t-t')} + \frac{\gamma_w \phi_w x_i}{\gamma_w (\phi_w x - 1) + \gamma_u} \left( e^{\gamma_w (\phi_w x - 1)(t-t')} - e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')} \right) + 1$$

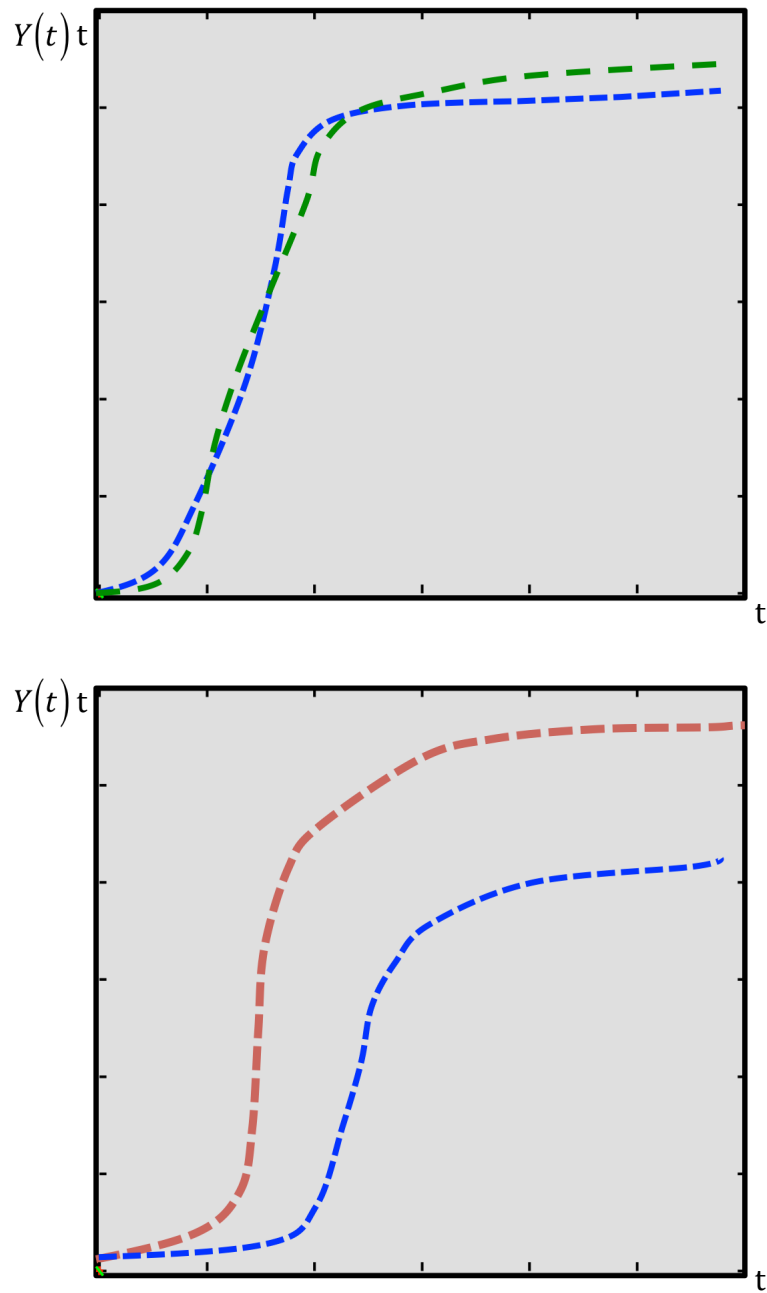


Figure 52 Trees Topology (Cumulative number of WOM volume in the overall networks - (a) includes 11,207 nodes (b) 1,291,352 nodes)

|     |  |  |
|-----|--|--|
|     | root-mean-square<br>deviation<br>(RMSD)-sample fit | mean absolute<br>percentage error<br>(MAPE)-sample fit |
| (a) | 1.32   | 0.32   |
| (b) | 6.08   | 0.65   |

Table 23 Data Fitting Performance of Tree Topology Models

| Parameter | Online social<br>network sites | $\beta$ | $\theta$ (%) | $\varphi_u$ | $\varphi_w$ | $\frac{1}{\gamma_w}$ | $\frac{1}{\gamma_u}$ |
|-----------|--------------------------------|---------|--------------|-------------|-------------|----------------------|----------------------|
| Parameter | (a)twitter                     | 3.45    | 8.04         | 0.13        | 0.27        | 6.22                 | 4.12                 |
| Estimates | (b)weibo                       | 4.76    | 11.21        | 0.09        | 0.16        | 4.01                 | 2.92                 |

Table 24 parameter estimates for tree topology model

Using the procedures as described in the previous chapter, the model parameters were estimated, which were subsequently plugged into Equations to predict the EWOM volume development. Here the purpose is not to compare the examples of Twitter and Weibo, but to apply the models in different context and assess the performance. According to the results, with the tree topology model as benchmark for complex network topology models in the following parts of the thesis,,the root-mean-square deviation (RMSD)-sample fit was 1.32 for the twitter example, and 6.08 for the weibo example. The root-mean-square deviation (RMSD) is a frequently used measure of the differences between values (sample and population values)



predicted by a model or an estimator and the values actually observed.. The RMSD represents the sample standard deviation of the differences between predicted values and observed values. The RMSD for the predictions of WOM volume development on Weibo is not satisfactory with the tree topology model. The mean absolute percentage error (MAPE) is a measure of prediction accuracy of a forecasting method in statistics, in this case in trend estimation. The mean absolute percentage error (MAPE) for Twitter example is 0.32 and it is 0.65 for Weibo example. Overall the tree topology model failed to predict the Weibo example. Furthermore,  $\varphi_u$  enote the probability of retweeting/reblogging upon seeing the tweet/weibo posted by viral source. This means that based on this tree topology model, such probability is 0.13 for twitter participants and 0.09 for Weibo participant., On the other hand,  $\varphi_w$  denotes the probability of retweeting/reblogging upon seeing the tweet/weibo posted by seeding source and based on the result, the predictions from tree topology model is that the probability was 0.27 for twitter participants and 0.16 for Weibo participants.

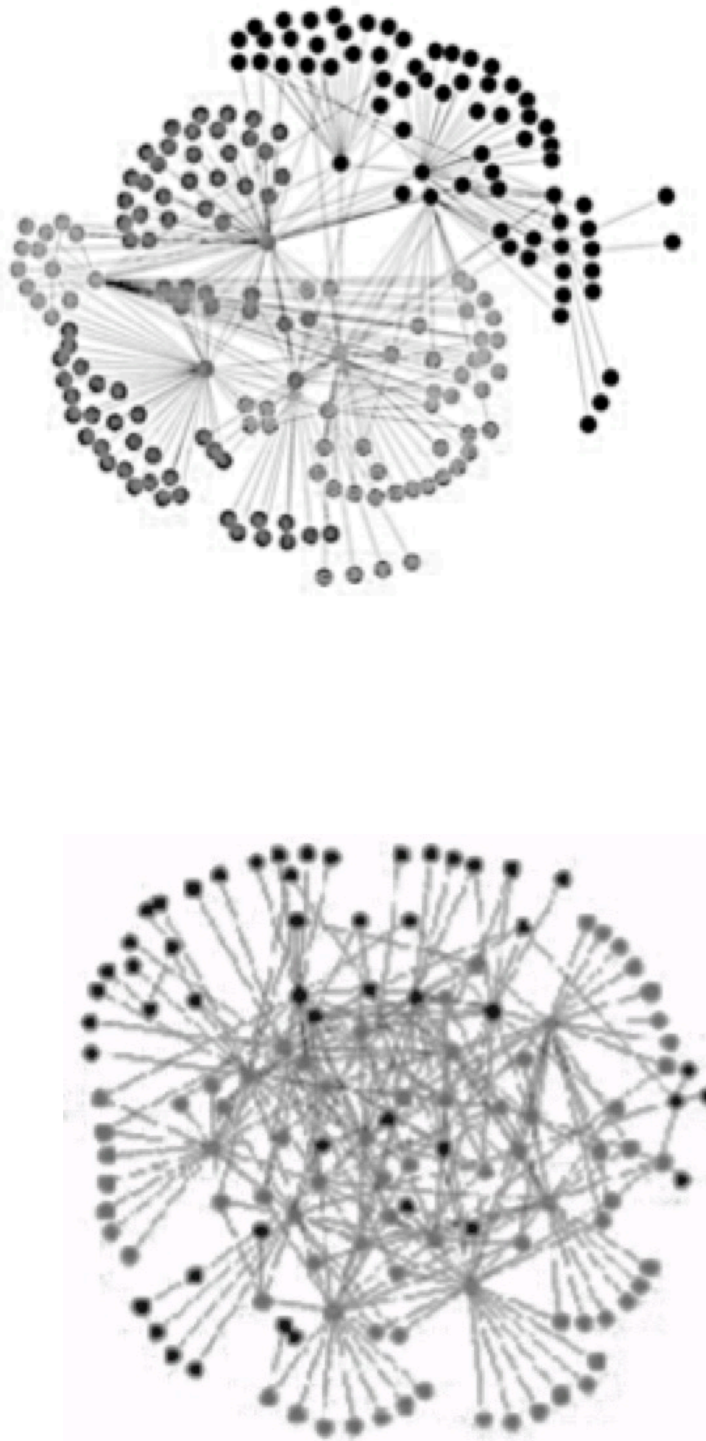


Figure 53 Scale Free Topology

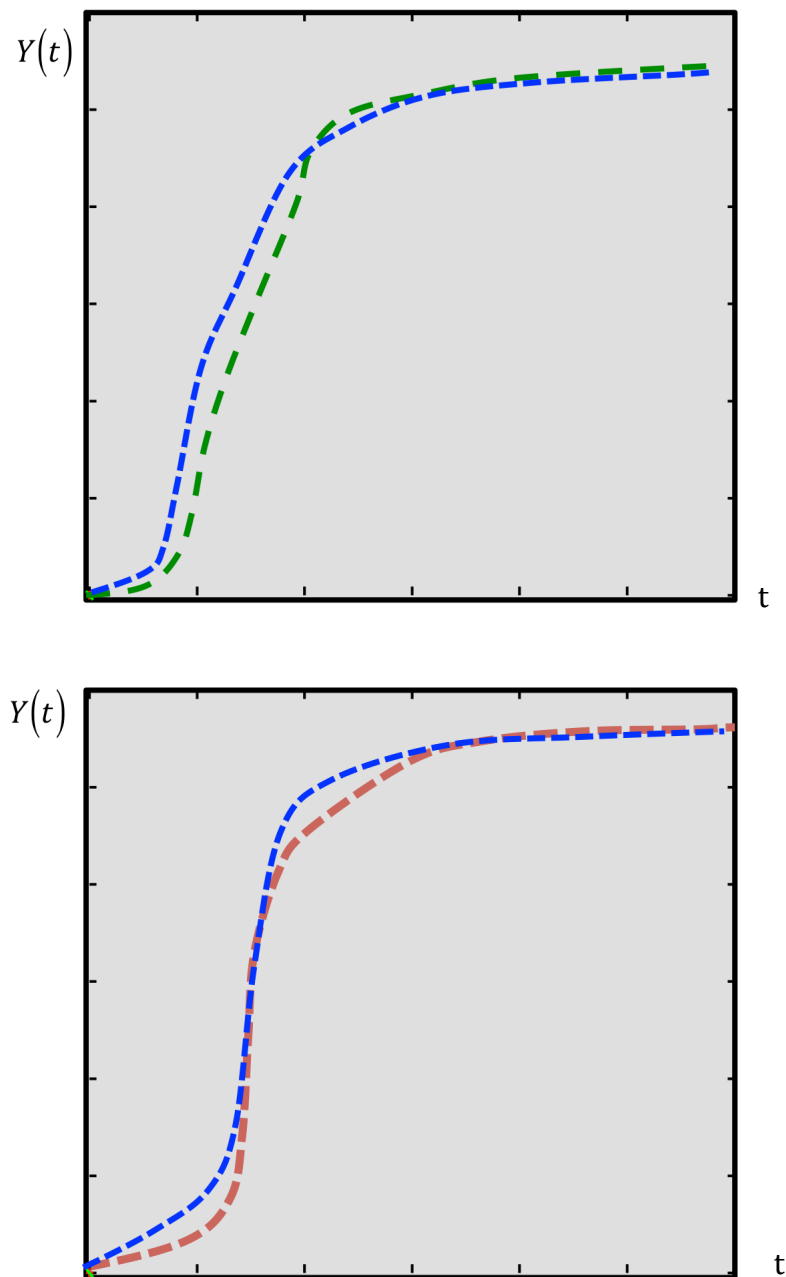


Figure 54 Scale-free (Cumulative number of WOM volume in the overall  
networks - (a) includes 11,207 nodes (b) 1,291,352 nodes)

Write the entropy rate of an unbiased walk on a network with degree

distribution  $P_k$  as  $h = \frac{N}{2K} \sum_k k P_k \ln(k) = \frac{\langle k \ln(k) \rangle}{\langle k \rangle}$ . In this case of SF networks

of size N the value of h can be easily expressed as a function of  $\gamma$  and N

taking into account that the maximum degree of the network is

$k_{\max} \sim k_0 N^{\frac{1}{\gamma-1}}$ , with  $k_0$  being the minimum degree of a node.

$$h(\gamma, N) = \ln(k_0) + \frac{1}{\gamma-2} + \frac{N^{(2-\gamma)(\gamma-1)} \ln(N)}{(\gamma-1)(N^{(2-\gamma)(\gamma-1)} - 1)}$$

|     | root-mean-square<br>deviation<br>(RMSD)-sample fit | mean absolute percentage<br>error (MAPE)-sample fit |
|-----|--|---|
| (a) | 0.71   | 0.32  |
| (b) | 0.64   | 0.11  |

Table 25 Data Fitting Performance of Scale Free Models

| Parameter | Online social<br>network sites | $\beta$ | $\theta$ (%) | $\varphi_u$ | $\varphi_w$ | $\frac{1}{\gamma_w}$ | $\frac{1}{\gamma_u}$ |
|-----------|--------------------------------|---------|--------------|-------------|-------------|----------------------|----------------------|
| Parameter | (a)twitter                     | 4.01    | 9.13         | 0.12        | 0.19        | 4.06                 | 4.03                 |
| Estimates | (b)weibo                       | 4.92    | 10.01        | 0.05        | 0.13        | 3.61                 | 2.33                 |

Table 26 Parameter Estimates for Scale Free Model

According to the results from the applications of models in scale-free network topology, root-mean-square deviation (RMSD) was 0.71 for twitter example and 0.64 for weibo example, which shows advantage over tree topology topology. On the other hand, the mean absolute percentage error (MAPE) was 0.32 for twitter example and 0.11 for weibo example. As the purpose is not to compare Twitter and Weibo, but to test the models in different social website, the scale-free topology model appear to show better fit the Weibo network.  $\varphi_u$  enote the probability of retweeting/reblogging upon seeing the tweet/weibo posted by viral source. This means that based on this tscale-free model, such probability is 0.12 for twitter participants and 0.05 for Weibo participant., On the other hand,  $\varphi_w$  denotes the probability of retweeting/reblogging upon seeing the tweet/weibo posted by seeding source and based on the result, the predictions from tree topology model is that the probability was 0.19 for twitter participants and 0.13 for Weibo participants.

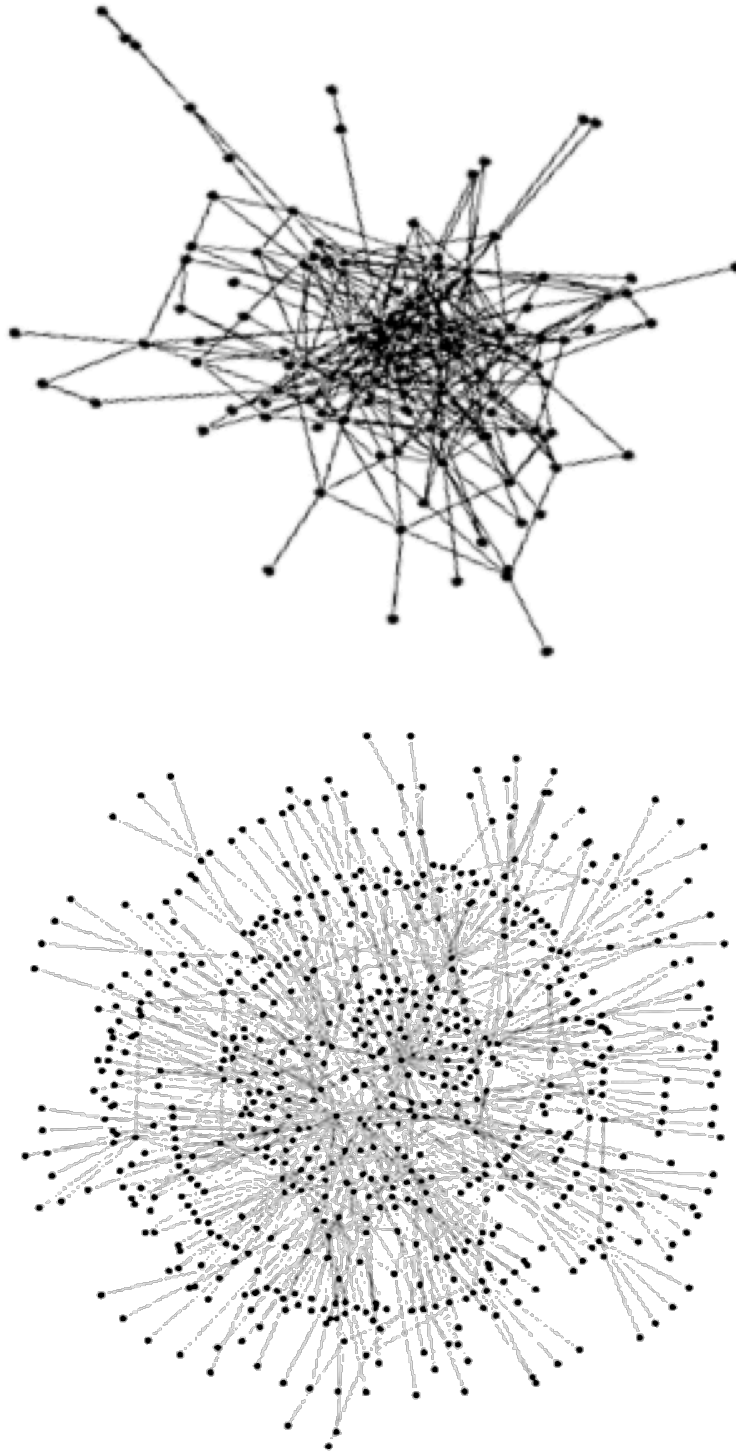


Figure 55 Random Network Topology

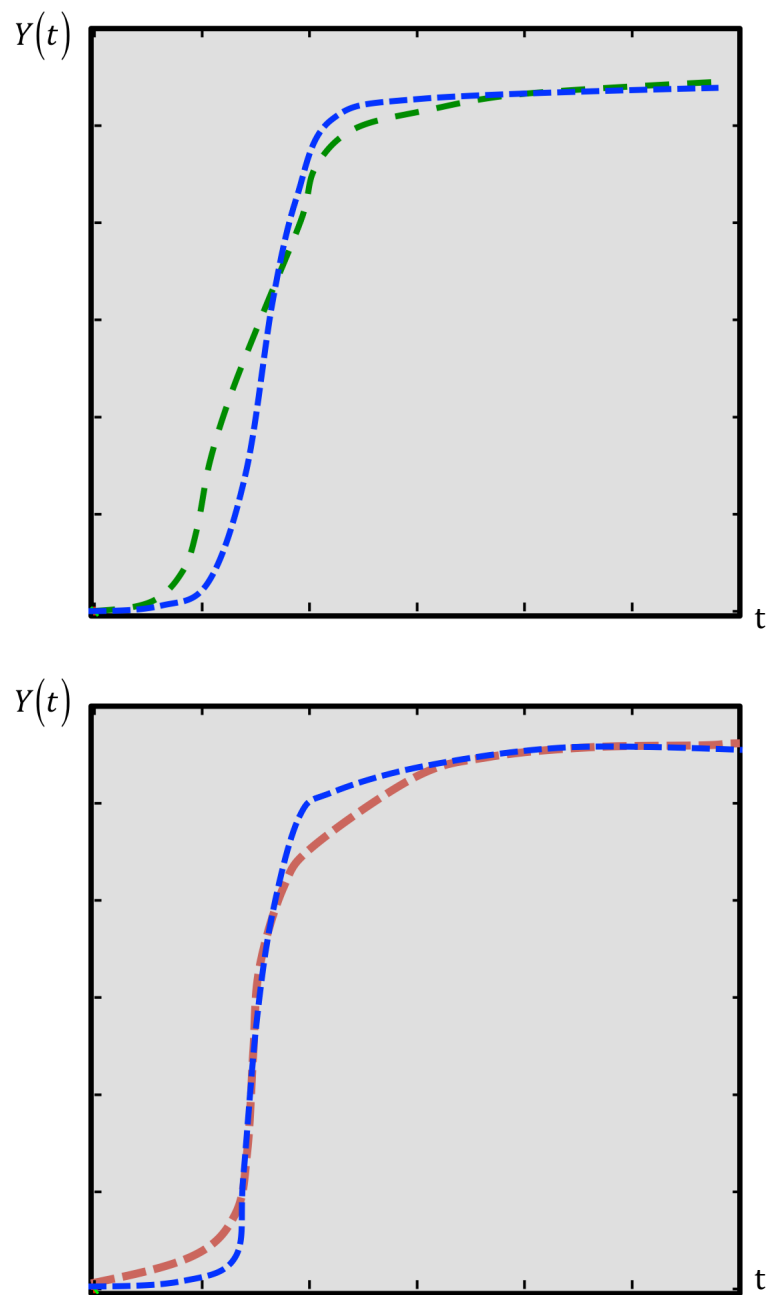


Figure 56 Random (Cumulative number of WOM volume in the overall  
networks - (a) includes 11,207 nodes (b) 1,291,352 nodes)

|     |  |   |
|-----|--|---|
|     | root-mean-square<br>deviation<br>(RMSD)-sample fit | mean absolute percentage<br>error (MAPE)-sample fit |
| (a) | 2.51   | 1.25  |
| (b) | 1.20   | 0.31  |

Table 27 Data Fitting Performance of Random Network Topology WOM  
Volume Model

| Parameter | Online social<br>network sites | $\beta$ | $\theta$ (%) | $\varphi_u$ | $\varphi_w$ | $\frac{1}{\gamma_w}$ | $\frac{1}{\gamma_u}$ |
|-----------|--------------------------------|---------|--------------|-------------|-------------|----------------------|----------------------|
| Parameter | (a)twitter                     | 3.65    | 5.13         | 0.35        | 0.52        | 5.33                 | 4.21                 |
| Estimates | (b)weibo                       | 4.07    | 6.01         | 0.29        | 0.41        | 4.26                 | 3.54                 |

Table 28 Parameter Estimates for Random Network Topology Model

According to the results from the applications of models in random network topology, root-mean-square deviation (RMSD) was 2.11 for twitter example and 1.20 for weibo example, which shows a slight disadvantage towards scale-free network topology model. On the other hand, the mean absolute percentage error (MAPE) was 1.25 for twitter example and 0.31 for weibo example. As the purpose is not to compare Twitter and Weibo, but to test the models in different social website, the random network topology model



appear to show better fit the Weibo network.  $\varphi_u$  enote the probability of retweeting/reblogging upon seeing the tweet/weibo posted by viral source. This means that based on this random network topologyg model, such probability is 0.35 for twitter participants and 0.29 for Weibo participant., On the other hand,  $\varphi_w$  denotes the probability of retweeting/reblogging upon seeing the tweet/weibo posted by seeding source and based on the result, the predictions from tree topology model is that the probability was 0.52 for twitter participants and 0.41 for Weibo participants.

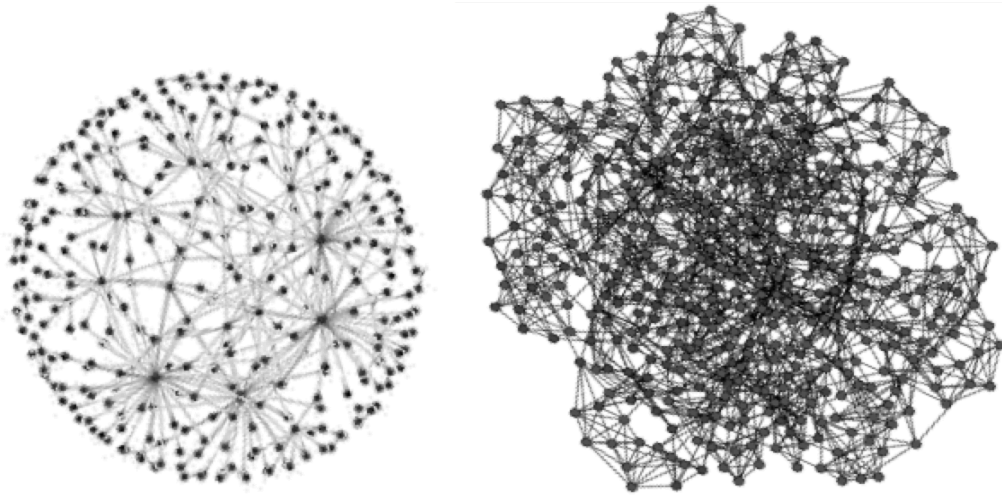


Figure 57 Small World Topology

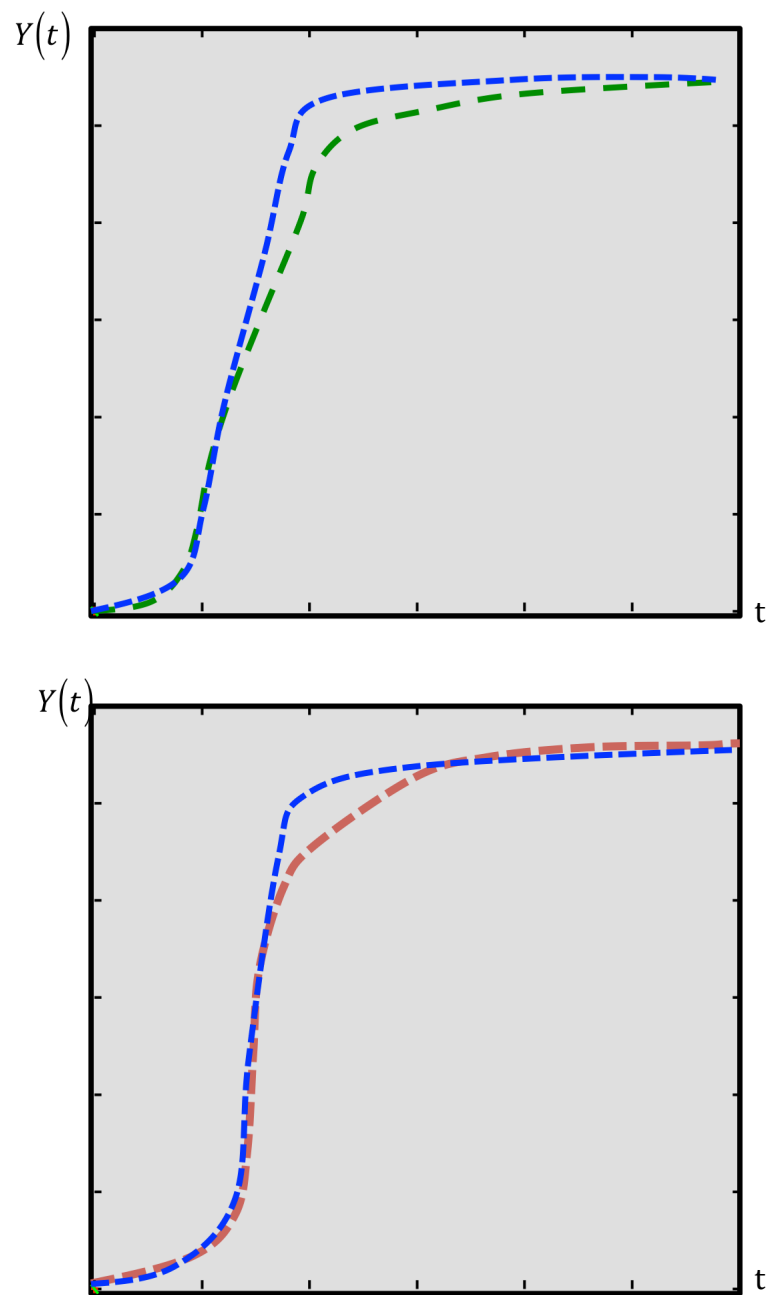


Figure 58 Small world (Cumulative number of WOM volume in the overall  
networks - (a) includes 11,207 nodes (b) 1,291,352 nodes)

|     |  |   |
|-----|--|---|
|     | root-mean-square<br>deviation<br>(RMSD)-sample fit | mean absolute percentage<br>error (MAPE)-sample fit |
| (a) | 0.82   | 1.25  |
| (b) | 0.95   | 2.06  |

Table 29 Data Fitting Performance of Small World Network Topology  
WOM Volume Model

| Parameter | Online social<br>network sites | $\beta$ | $\theta$ (%) | $\varphi_u$ | $\varphi_w$ | $\frac{1}{\gamma_w}$ | $\frac{1}{\gamma_u}$ |
|-----------|--------------------------------|---------|--------------|-------------|-------------|----------------------|----------------------|
| Parameter | (a)twitter                     | 8.14    | 9.43         | 0.41        | 0.56        | 3.12                 | 2.03                 |
| Estimates | (b)weibo                       | 9.47    | 11.32        | 0.32        | 0.43        | 3.01                 | 2.04                 |

Table 30 Parameter Estimates for Small World Network Topology Model

According to the results from the applications of models in small-worldnetwork topology, root-mean-square deviation (RMSD) was 0.82 for twitter example and 0.95 for weibo example, which shows advantage over tree topology topology. On the other hand, the mean absolute percentage error (MAPE) was 1.35 for twitter example and 2.06 for weibo example. As the purpose is not to compare Twitter and Weibo, but to test the models in different social website, the small world topology

model appear to show better fit the Weibo network.  $\varphi_u$  denote the probability of retweeting/reblogging upon seeing the tweet/weibo posted by viral source. This means that based on this tscale-free model, such probability is 0.41 for twitter participants and 0.32 for Weibo participant., On the other hand,  $\varphi_w$  denotes the probability of retweeting/reblogging upon seeing the tweet/weibo posted by seeding source and based on the result, the predictions from tree topology model is that the probability was 0.56 for twitter participants and 0.43 for Weibo participants.

In conclusion, we have

| Topology                        | WOM | Volume      | root-mean-square<br>deviation<br>(RMSD)-sample fit | mean<br>percentage<br>(MAPE)-sample fit | absolute<br>error |
|---------------------------------|-----|-------------|--|---|-------------------|
| Trees topology                  |     | (a) twitter | 1.32   | 0.32                                    |                   |
|                                 |     | (b) weibo   | 6.08   | 0.65                                    |                   |
| Scale-free<br>topology          |     | (a) twitter | 0.71   | 0.32                                    |                   |
|                                 |     | (b) weibo   | 0.64   | 0.11                                    |                   |
| Random network<br>topology      |     | (a) twitter | 2.51   | 1.25                                    |                   |
|                                 |     | (b) weibo   | 1.20   | 0.31                                    |                   |
| Small world<br>network topology |     | (a) twitter | 0.82   | 1.25                                    |                   |
|                                 |     | (b) weibo   | 0.95   | 2.06                                    |                   |

Table 31 Topology WOM Volume Models Displayed Good Fit in  
Computer Simulation

Overall, scale-free topology illustrated advantages over the other topologies as it has the best root-mean-square deviation (RMSD) sample fit and mean absolute percentage error (MAPE) sample fit.

## 4.2 DATA ANALYSIS AND DISCUSSION OF WOM VALENCE

For WOM valence data analysis, NVivo has been used to analysis and code qualitative data from the web crawling (figure 59). Beside this tweet from Katy Perry, more seeding tweets (130 seeding tweets on twitter) have been selected for the training of WOM valence ANN model. Katy Perry's tweet has then been used as a benchmark for assessing the performance of ANN model. An overview of the web crawling result has been shown in table 32.

Table 32 WOM Valence Overview of Katy Perry's Tweet (Neutral Ones  
Not Included)

|                               |  |
|-------------------------------|--|
| <b>Web Crawling Time span</b> | 21 <sup>th</sup> August 2012–<br>21 <sup>th</sup> October 2012 |
| Positive                      | 75.2%  |
| Negative                      | 24.8%  |

Table 33 WOM Valence Examples from Katy Perry's Tweet (Note:  
Reviews have overlaps regarding the valence stimuli and were coded  
accordingly)

|  |   |
|--|---|
| <b>Web Crawling – Content<br/>categorisation</b> | Examples  |
| Satisfaction                                     | Matthew Dark @magimat2755( 21 Aug<br>2012)<br><br>@katyperry funny thing I have seen in such<br>a long time |



NVivo has been used to analysis and code qualitative data from the web crawling (figure 60). Beside this weibo post from XIAOMI Phone, more seeding weibo posts (130 seeding posts on Weibo) have been selected for the training of WOM valence ANN model. XIAOMI phone's tweet has then been used as a benchmark for assessing the performance of ANN model.

Table 34 WOM Valence Overview of XIAOMI Weibo

|                               |   |
|-------------------------------|---|
| <b>Web Crawling Time span</b> | 21 <sup>th</sup> August 2012–<br>21 <sup>th</sup> December 2012 |
| Positive                      | 87.3%   |
| Negative                      | 12.7%   |

Table 35 WOM Valence Examples from Xiaomi Weibo (Note: Reviews have overlaps regarding the valence stimuli and were coded accordingly)

| <b>Web Crawling – Content categorisation</b> | <b>Examples</b>  |
|--|--|
| Satisfaction                                 |  <p>某某小西 ★👑: 微博专卖。噢耶~ @西易轩<br/>2012-12-19 09:57</p> <p>“Oh great! Exclusively on Weibo.”</p>  |
| Loyalty                                      |  <p>杰克吴昌松 👑: @小米手机, 我爱小米, 我到现在买了七部小米手机了, @姚晨<br/>2012-12-19 09:58</p> <p>“I love XIAOMI phone. I've already bought seven XIAOMI phones”</p> |
| Quality                                      |  <p>有着深痕的木子: 小米其实还不错~<br/>2012-12-19 09:56</p> <p>“XIAOMI phone is actually quite good”</p>   |



|                 |  |
|-----------------|--|
| Commitment      |  <p>“I’m so proud of XIAOMI phone”</p>  <p>“I know I may not get the prize, but I just want to show my support for XIAOMI phone”</p> |
| Trust           |  <p>“This is fake. Show us the lists of names who have won the free phones.”</p>   |
| Perceived Value |  <p>“Good value for money. Sold on Weibo first hahaha.”</p>   |

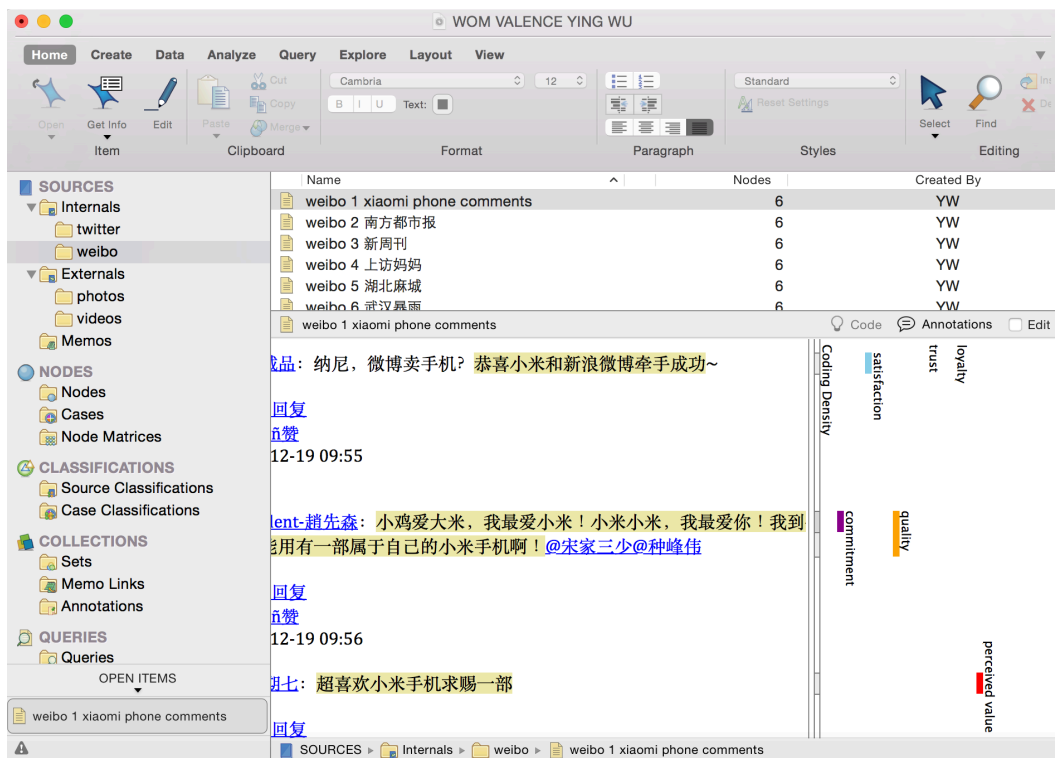


Figure 60 NVivo Screenshot of Qualitative Data Analysis (Weibo)

The main advantage of neural networks is that it is possible to train a neural network to perform a particular function by adjusting the values of connections (weights) between elements. Artificial neural networks (ANN) have memory. The memory in neural networks corresponds to the weights in the neurons. Neural networks can be trained offline and then transferred into a process where adaptive learning takes place. In our case, a neural network controller could be trained to predict the WOM valence value in the simulink environment. After training with real data set crawled from social website, the network weights are set. The ANN is placed in a feedback loop with the actual WOM valence decision process. The network will also adapt the weights to improve performance as it apply to social network WOM valence prediction in the future. The process is illustrated in the flow chart below (Figure 37).

The main disadvantage of ANN is they operate as black boxes. The rules of operation in neural networks are completely unknown. It is not possible to convert the neural structure into known model structures.

As discussed in chapter 2, the input variables are shown in the table.

| Inputs | Meaning         |
|--------|-----------------|
| $I_1$  | Satisfaction    |
| $I_2$  | Loyalty         |
| $I_3$  | Quality         |
| $I_4$  | Commitment      |
| $I_5$  | Trust           |
| $I_6$  | Perceived Value |

Table 36 The Six Input Layer Nodes of the ANN Model for WOM Valence Predictive Modeling

### ***Training Algorithm for the Modeling of WOM valence***

#### **Phase 1 – Initialization of weights**

Step 1: Initialize the weights, biases and learning rate to small random values.

Step 2: Perform steps 3-10 when stopping condition is false.

Step 3: Perform steps 4-9 for each training pair.

#### **Phase 2 – Feed forward phase**

Step 4: Each input unit receives input signal  $I_m$  ( $m=1$  to 6). And sends it to the hidden unit.

Step 5: Each hidden unit  $H_n$  ( $n= 1$  to  $p$ ) sums its weighted input signals to calculate net input

$$Hin_n = v_{0n} + \sum_{m=1}^{m=6} I_m v_{mn}$$

Calculate the output of the hidden unit by applying its binary sigmoidal activation function over  $Hin_n$

$$H_n = f(Hin_n) = \frac{1}{1 + e^{-Hin_n}}$$

and send the output signal from the hidden unit to the input of the output layer units.

Step 6: For each output unit  $y$ , calculate the net input

$$yin = w_0 + \sum_{n=1}^{n=6} z_n w_n$$

and its binary sigmoidal activation function is applied to compute the output signal.

$$y = f(yin) = \frac{1}{1 + e^{-yin}}$$

### **Phase 3 – Back propagation of error**

Step 7: Output unit  $y$  receives a target pattern corresponding to the input training pattern and computes the error correction term.

$$\delta = (t - y) f'(yin)$$

On the basis of the calculated error correction term update the change in weights and bias

$$\Delta w_n = \alpha \delta H_n$$

$$\Delta w_0 = \alpha \delta$$

Also send  $\delta$  to the hidden layer backwards.

Step 8: Each hidden unit sums its delta inputs from the output units.

$$\delta_{inn} = \delta w_n$$

The term  $\delta_{inn}$  gets multiplied with the derivative of  $f(H_{inn})$  to calculate the error term

$$\delta_n = \delta_{inn} f'(H_{inn})$$

On the basis of  $\delta_n$  update the change in weights and bias

$$\Delta v_{mn} = \alpha \delta_n I_m$$

$$\Delta v_{on} = \alpha \delta_n$$

#### **Phase 4 – Weights and bias update**

Step 9: Output unit updates the bias and weights

$$w_n(new) = w_n(old) + \Delta w_n$$

$$w_0(new) = w_0(old) + \Delta w_0$$

Each hidden unit updates its bias and weights

$$v_{mn}(new) = v_{mn}(old) + \Delta v_{mn}$$

$$v_{0n}(new) = v_{0n}(old) + \Delta v_{0n}$$

Step 10: Check for the stopping condition. The stopping condition be the certain number of epochs.

### ***Testing Algorithm for the modeling of WOM valence***

#### **Phase 1 – Initialization of weights**

Step 1: Weights and bias to be used are taken from the training algorithm.

Step 2: Perform steps 3-6 for each input vector.

#### **Phase 2: Feed forward phase**

Step 3: Set the activation of input unit  $I_m$  (m=1 to 6).

Step 4: Calculate the net input to the hidden unit  $H$  and its output for n=1 to p.

$$Hin_n = v_{0n} + \sum_{m=1}^{m=6} I_m v_{mn}$$

$$H_n = f(Hin_n) = \frac{1}{1 + e^{-Hin_n}}$$

Step 5: Compute the output of the output layer unit

$$yin = w_0 + \sum_{n=1}^p H_n w_n$$

$$y = f(yin) = \frac{1}{1 + e^{-yin}}$$

Binary sigmoidal activation function is used for calculating the output.

Step 6: Calculate the response

If  $y = t$

    Response is positive

Else

    Response is negative

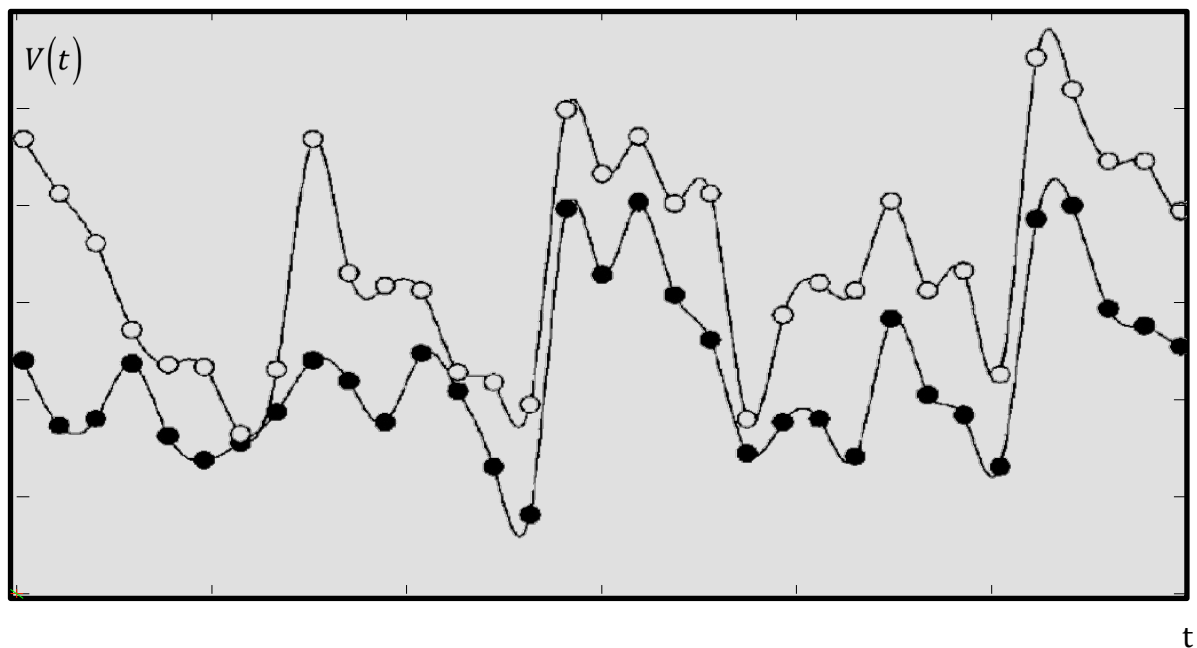


Figure 61 Twitter Valence Data Fitting

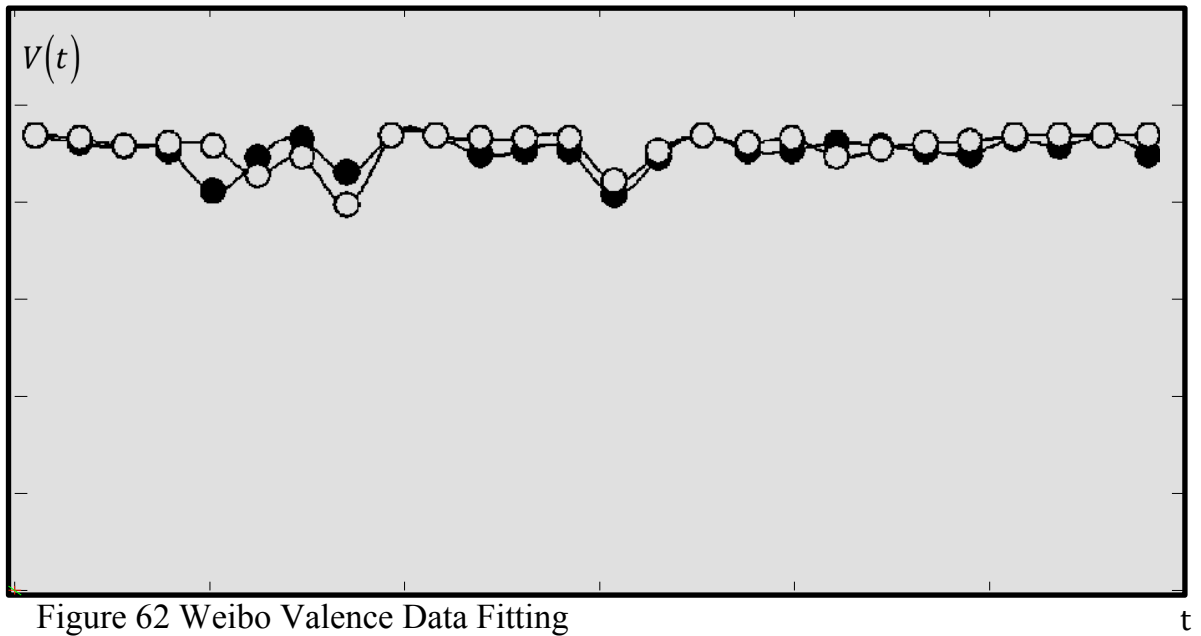


Figure 62 Weibo Valence Data Fitting

|     | root-mean-square<br>deviation<br>(RMSD)-sample fit | mean absolute percentage<br>error (MAPE)-sample fit |
|-----|--|---|
| (a) | 4.82   | 2.07  |
| (b) | 0.98   | 0.21  |

Table 37 Twitter Data Fitting –WOM Valence

Performance results show estimation of WOM valence at a high accuracy level of more than 70%. The root-mean-square deviation (RMSD) is 4.82 for Twitter example and 0.98 for Weibo example. The mean absolute percentage error (MAPE) is 2.07 for Twitter example and 0.21 for Weibo



example. The ANN model appear to perform better in the predictions for Weibo.. The purpose is not to compare Twitter and Weibo, but to test how the model perform in different social network context. Overall, the ANN models displayed good fit in computer simulation

#### 4.3 CHAPTER SUMMARY

The findings answer the research questions regarding the modeling of WOM volume and WOM valence and the models illustrated good fit in computer simulations.

## **CHAPTER FIVE**

### **CONCLUSION**

#### **5.1 MAIN CONTRIBUTIONS OF THE STUDY**

The discussions of main contributions of the study include key findings from the study and key contributions from theoretical, practical and empirical perspectives.

##### **5.1.1 KEY FINDINGS FROM THE STUDY**

Inspired by network topology models (branching process) and social network studies in previous literature regarding WOM volume for viral marketing campaigns, This research propose WOM volume models using complex network topologies and compares the performance of various complex network topology models for WOM volume growth, benchmarked with data crawled from social websites. The models performed well and these dynamic modeling approaches extend the scientific knowledge in the topic as most of the WOM studies were using traditional structural equation modeling approach. Moreover, this sort of knowledge may also be valuable for practitioners as well because the proposed WOM volume models predict the growth of WOM volume over time in social networks, thus marketers can select and seed agents at different timing accordingly for a more

successful WOM and viral marketing campaign achieving high WOM volume. This thesis identifies factors in the literature review that are helpful to motivate initial WOM activities (the cause of WOM volume) and the effects of WOM and viral marketing (the outcome of WOM volume). Furthermore, this thesis use mathematical models and computer experimental simulations and therefore contribute to the literature regarding the research methodology in WOM marketing. Web crawling the social websites for data collection is also brand new to this area of research and contribute to the exiting literature.

The present thesis has studied WOM valence modeling from a brand new perspective in this field, which is the artificial neural network modeling. This study has shown that with the artificial neural network modeling approach, consumer behavior (WOM valence decision) can arise from input stimuli, learning and output functions. The fact that the model can process multi-valued stimuli allows it to be built in conformity with biological neural models dynamics (Gerstner & Kistler, 2002 ). Furthermore, the artificial neural network model displayed good fit in computer simulation and training that the result is consistent with expected outcome in psychology. As a result, the ANN model may help researchers and marketers alike and control WOM marketing activities regarding the stimuli to achieve positive WOM valence in WOM and viral marketing..

For the modeling WOM volume, the predicted number of social network site users who retweet / reblog the seeding tweet/weibo after the seeding post be presented on that user's social networking site page.

$$f(U(t)|U(t')=i_u)=i_u e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')}$$

The predicted number of social network site users who retweet / reblog the SEEDING tweet/weibo after the seeding post be presented on that user's social networking site page.

$$f(W(t)|W(t')=i_w)=i_w e^{\gamma_w (\varphi_w^x - 1)(t-t')} \\ \frac{\gamma_w \varphi_w^x i_w}{\gamma_w (\varphi_w^x - 1) + \gamma_u} \left( e^{\gamma_w (\varphi_w^x - 1)(t-t')} - e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')} \right) +$$

The predicted cumulative number of EWOM volume on a social website in the EWOM volume development process at time  $t$

$$f(Y(t)|Y(t')=i_y)=i_y e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')} \\ + i_w e^{\gamma_w (\varphi_w^x - 1)(t-t')} + \frac{\gamma_w \varphi_w^x i_w}{\gamma_w (\varphi_w^x - 1) + \gamma_u} \left( e^{\gamma_w (\varphi_w^x - 1)(t-t')} - e^{\binom{n-1}{k} p^k (1-p)^{n-1-k} (t-t')} \right) + 1$$

Table 38 illustrated the variables used for the modeling of WOM volume

|                       |  |
|-----------------------|--|
| $t \in [0, \dots, T]$ | Denote continuous time, with $t=0$ as the start and $t=T$ the end of the EWOM volume development process |
|-----------------------|--|

|               |   |
|---------------|---|
| $Y(t)$        | Denote the cumulative number of EWOM volume on a social website in the EWOM volume development process at time $t$  |
| $U(t)$        | Denote the number of social network site users who retweet / reblog the SEEDING tweet/weibo after the seeding post be presented on that user's social networking site page. |
| $W(t)$        | Denote the number of social network site users who retweet / reblog the VIRAL tweet/weibo yet after the viral post be presented on that user's social networking site page. |
| $G(t)$        | Denote the vector $[U(t), W(t), Y(t)]$  |
| $s$           | Denote all the retweeting and reblogging sources.<br>i.e. $s \in \{\text{seeding posts, viral posts}\}$   |
| $\beta$       | Denote the average number of retweets/reblogs a participant gets.   |
| $\phi_{12}^s$ | Denote the probability of retweeting/reblogging upon seeing the tweet/weibo posted by source $s$  |
| $1/\gamma_u$  | Denote the average time between a seeding post be posted and be retweeted/reblogged   |
| $1/\gamma_w$  | Denote the average time between a viral post be posted and be retweeted/reblogged   |

Table 38 The Variables Used for the Modeling Of WOM Volume

For the modeling of WOM valence,

| Inputs | Meaning         |
|--------|-----------------|
| $I_1$  | Satisfaction    |
| $I_2$  | Loyalty         |
| $I_3$  | Quality         |
| $I_4$  | Commitment      |
| $I_5$  | Trust           |
| $I_6$  | Perceived Value |

Table 39 The Input Variables Used For The Modeling Of WOM Valence

### **Phase 1 – Initialization of weights**

Step 1: Initialize the weights, biases and learning rate to small random values.

Step 2: Perform steps 3-10 when stopping condition is false.

Step 3: Perform steps 4-9 for each training pair.

### **Phase 2 – Feed forward phase**

Step 4: Each input unit receives input signal  $I_m$  ( $m = 1$  to 6). And sends it to the hidden unit.

Step 5: Each hidden unit  $H_n$  ( $n = 1$  to  $p$ ) sums its weighted input signals to calculate net input

$$Hin_n = v_{0n} + \sum_{m=1}^{m=6} I_m v_{mn}$$

Calculate the output of the hidden unit by applying its binary sigmoidal activation function over  $Hin_n$

$$H_n = f(Hin_n) = \frac{1}{1 + e^{-Hin_n}}$$

and send the output signal from the hidden unit to the input of the output layer units.

Step 6: For each output unit  $y$ , calculate the net input

$$yin = w_0 + \sum_{n=1}^{n=6} z_n w_n$$

and its binary sigmoidal activation function is applied to compute the output signal.

$$y = f(yin) = \frac{1}{1 + e^{-yin}}$$

### Phase 3 – Back propagation of error

Step 7: Output unit  $y$  receives a target pattern corresponding to the input training pattern and computes the error correction term.

$$\delta = (t - y) f'(yin)$$

On the basis of the calculated error correction term update the change in weights and bias

$$\Delta w_n = \alpha \delta H_n$$

$$\Delta w_0 = \alpha \delta$$

Also send  $\delta$  to the hidden layer backwards.

Step 8: Each hidden unit sums its delta inputs from the output units.

$$\delta_{inn} = \delta w_n$$

The term  $\delta_{inn}$  gets multiplied with the derivative of  $f(H_{inn})$  to calculate the error term

$$\delta_n = \delta_{inn} f'(H_{inn})$$

On the basis of  $\delta_n$  update the change in weights and bias

$$\Delta v_{mn} = \alpha \delta_n I_m$$

$$\Delta v_{on} = \alpha \delta_n$$

#### **Phase 4 – Weights and bias update**

Step 9: Output unit updates the bias and weights

$$w_n(new) = w_n(old) + \Delta w_n$$

$$w_0(new) = w_0(old) + \Delta w_0$$

Each hidden unit updates its bias and weights

$$v_{mn}(new) = v_{mn}(old) + \Delta v_{mn}$$

$$v_{on}(new) = v_{on}(old) + \Delta v_{on}$$

Step 10: Check for the stopping condition. The stopping condition be the certain number of epochs.

#### ***Testing Algorithm for the modeling of WOM valence***

##### **Phase 1 – Initialization of weights**

Step 1: Weights and bias to be used are taken from the training algorithm.

Step 2: Perform steps 3-6 for each input vector.



## Phase 2: Feed forward phase

Step 3: Set the activation of input unit  $I_m$  (m=1 to 6).

Step 4: Calculate the net input to the hidden unit  $H$  and its output for  
n=1 to p.

$$Hin_n = v_{0n} + \sum_{m=1}^{m=6} I_m v_{mn}$$

$$H_n = f(Hin_n) = \frac{1}{1 + e^{-Hin_n}}$$

Step 5: Compute the output of the output layer unit

$$yin = w_0 + \sum_{n=1}^p H_n w_n$$

$$y = f(yin) = \frac{1}{1 + e^{-yin}}$$

Binary sigmoidal activation function is used for calculating the output.

Step 6: Calculate the response

If  $y = t$

### 5.1.2 KEY THEORETICAL CONTRIBUTIONS

The study has made key theoretical contributions to the literature. This study has looked at the cause, development and outcome of Word-of-Mouth Marketing: with particular reference to WOM volume, valence and the modeling of viral marketing. According to previous literature on WOM volume, the cause, development and outcome of WOM volume in social networks are significantly influenced by network topologies. Theoretically, based on Kozinets et al (2010), there are three theoretical topology models currently coexisting regarding WOM marketing, and each pertains to different circumstances. They are the Organic Interconsumer Influence Model (point to point topology), the Linear Marketer Influence Model (tree topology) and the Network Coproduction Model (complex network topology). Nevertheless, the existing WOM volume models are all structural equation models except the predictive tree topology model developed by Van der Lans et al. (2010). The mathematical tree topology model was theoretically based on the Linear Marketer Influence Model that could represent limited types of EWOM and WOM marketing such as E-mail based EWOM marketing campaigns. Thus Van der Lans (2010) tree topology model is the first mathematical topology model corresponding to the theoretical Linear Marketer Influence Model. There have been several similar tree topology models developed since, and they were all tree

topology models using email EWOM marketing (such as Iribarren and Moro, 2011). This study looked at social networking sites instead of emails. Moreover, the theoretical Network Coproduction Model mainly represents EWOM marketing such as viral marketing in social networking sites; and there had been no mathematical model developed before this study to predict the EWOM volume using the Network Coproduction Model. Thus this study is the first research on developing mathematical complex network topology model for predictions on EWOM volume in social networking sites corresponding the Network Coproduction Model. On the other hand, according to previous literature on WOM valence, the cause of WOM valence includes satisfaction, loyalty, quality, commitment, trust and perceived value. The existing models were all structural equation models before this study and they did not include these six factors all in once. There have been no predictive models developed for WOM valence before this study. Thus this study is the first research on developing predictive model for inspecting the WOM valence development process and making predictions of EWOM valence outcome in social networking sites.

### 5.1.3 KEY PRACTICAL CONTRIBUTIONS

This study has made key practical contributions in the field of WOM and in viral marketing on social networking sites in particular. The practical contributions include the computer experimental design process, web-crawling data collection methods, and simulation experiments that could be applied in future research; practical contributions of this study also include the applications of new WOM volume and WOM valence models because the models will help researchers and marketers to predict WOM volume and WOM valence in social networking sites word-of-mouth marketing and make relevant campaign decisions accordingly.

### 5.1.4 KEY EMPIRICAL CONTRIBUTIONS

The study has made key empirical contributions in developing predictive WOM volume and predictive WOM valence models. There had been no predictive models of WOM volume or WOM valence in social networking sites ever be developed by researchers or marketers prior to this study. Thus developing these predictive models fills the gaps of empirical development. The mathematical model for predicting WOM volume developed in this study corresponds to the theoretical Network Coproduction Model. There

had been no mathematical model developed using this theoretical model before this study. This model emphasizes the interrelationships among social networks, unlike the linear relationships in the Linear Marketer Influence Model. In this study, complex network topology model was developed and tested as the first mathematical model for this nonlinear Network Coproduction Model. The gangnam style tweet and the xiaomi phone weibo were used to develop the network topology model and run the computer simulation experiments. Input variables used in the artificial neural network model of WOM valence were identified and gathered through the literature review. Information of 130 tweets and 130 weibo posts were collected using web crawlers for training the artificial neural network model of WOM valence and then the gangnam style tweet and the xiaomi phone weibo were used to test the ANN model. These model development processes were new to the exiting empirical model developments of WOM volume and WOM valence and thus have made contributions to the field of empirical research.

## 5.2 MANAGERIAL IMPLICATIONS

WOM and Viral marketing are not necessarily an art rather than a science; marketers can improve their campaigns by using WOM volume and WOM valence models to predict the outcome of their WOM and viral marketing campaigns. This research is the first time to use complex network for WOM volume modeling and is also the first time to use artificial neural network for WOM valence modeling. Such dynamic modeling approach can be further applied in the future for researchers and practitioners alike.

Marketers and managers can use the WOM volume development model and WOM valence development model developed in this study for predicting and managing the online WOM campaign, monitoring, adjusting and adapting marketing activities based on the forecast made by the models.

### 5.3 LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Although the study has reached its objectives, there were limitations.

Firstly, there were the sample limitations. For WOM volume, the sample has taken the form of non-probability sampling - which was the judgement sampling. The sample was selected on the basis of what the researcher thought those particular sample units would contribute to the development of WOM volume models. The gangnam style tweet and the xiaomi phone weibo were selected, as they were acknowledged to be by far the most successful viral posts in the corresponding social networking sites (twitter and weibo) and thus the sample was not biased by the opinion of the researcher. However, the sample was limited because it only includes posts from twitter and weibo. There were many more social networking sites such as Facebook, YouTube and Instagram that could have been considered, but due to the time frame and the features of the social networking sites, only twitter and weibo were selected. For WOM valence, judgement sampling was used. The sample selected using the judgement sampling method for the testing stage of the ANN model was identical with the WOM volume sample and thus had the same shortcomings. 130 top tweets and 130 top weibo posts were selected for the training stage of the ANN model based on the ranking of numbers of re-tweets/reposts in

2012. A larger number of tweets and weibo posts would have improved the performance of the model. Nevertheless, the time frame was limited and the number of the sample units was sufficient for the training stage of the ANN model. For further research, more social networking sites should be included in the sample and a larger number of sample units would contribute towards the performance of WOM volume and WOM valence models.

Secondly, the scope of the discussions was limited. The majority of the discussions were restricted to topics related to WOM volume and WOM valence as this study aimed to develop predictive models of WOM volume and WOM valence. Further discussions such as research relating WOM to financial performance could extend the scope of discussions. Furthermore, this study only applied the models in different social networking sites to test the models; it did not compare the two different cases selected in these two social websites because the comparison of different social networking sites was not the objective of this study; WOM performance in different social networking sites could be compared and discussed in the future. Moreover, researchers and marketers alike could investigate how marketing activities affects the model performance in future research.



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## Appendix

The figure displays two screenshots of a web crawling tool interface, showing different configuration options.

**Top Screenshot (Basic Option):**

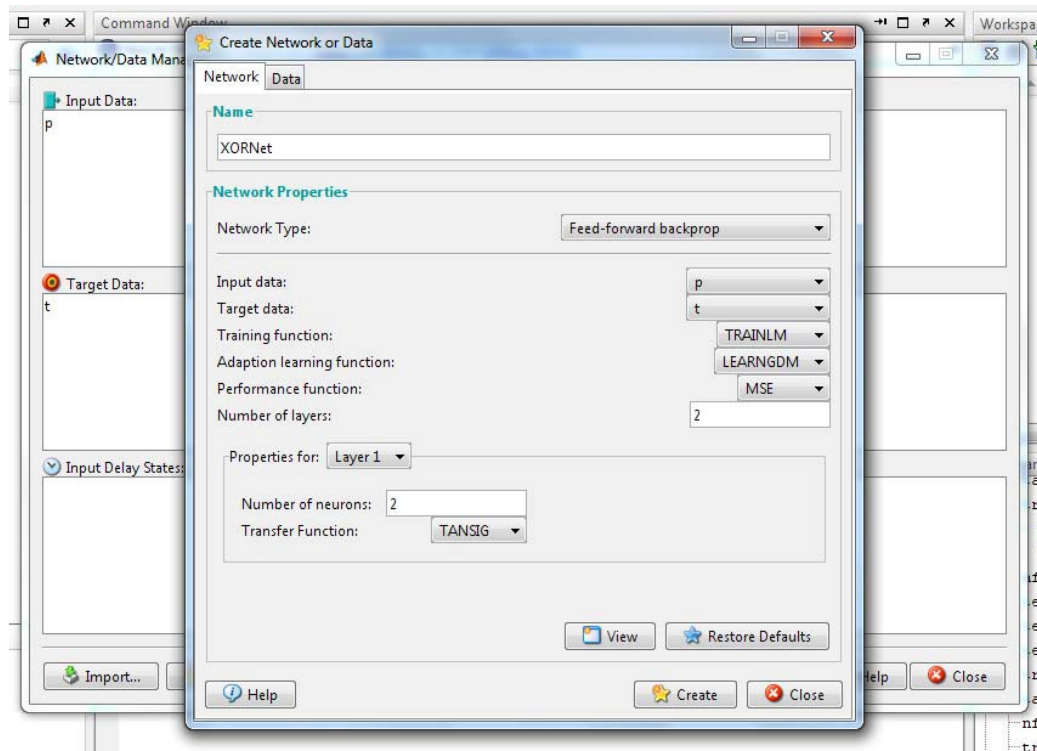
- Tab: **Basic Option** (selected), Filtering Option
- Seed ID:
- + Add, - Remove
- ConsumerKey:
- ConsumerSecret:
- AccessToken:
- AccessTokenSecretKey:
- + Add, - Remove
- Start Analysis, Start Gathering, Stop Gathering

**Bottom Screenshot (Filtering Option):**

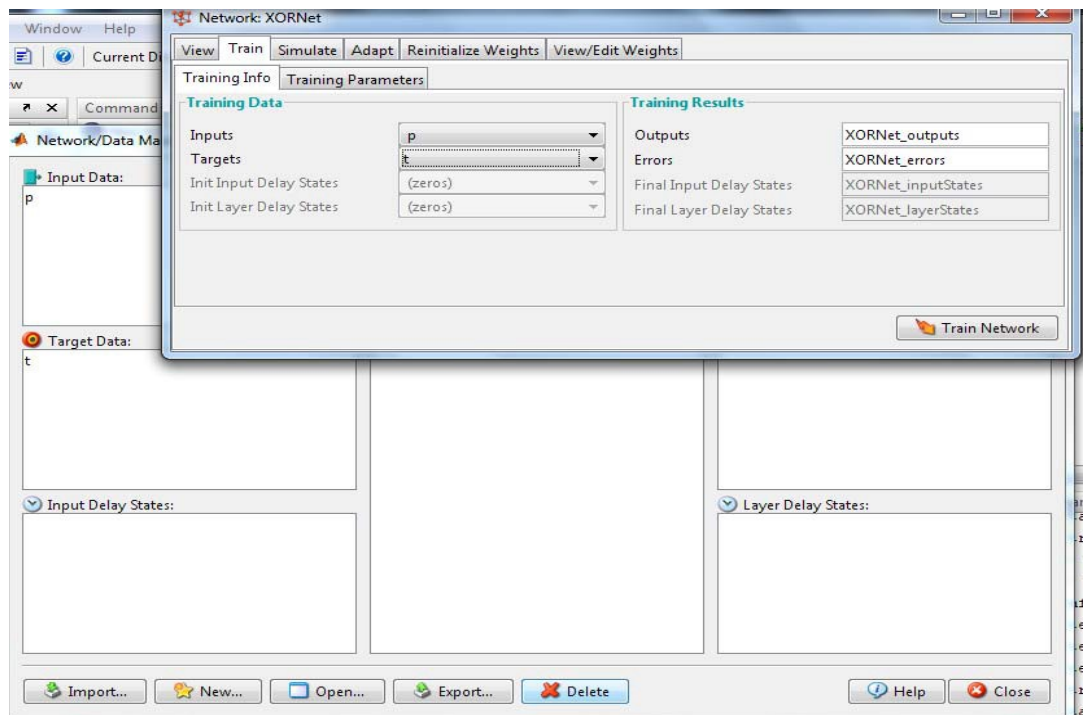
- Tab: Basic Option, **Filtering Option** (selected)
- Rule Name:
- + Add, - Remove
- Rule Name:
- Keyword:
- + Add, - Remove
- Start Analysis, Start Gathering, Stop Gathering

Appendix Figure Web crawling tool



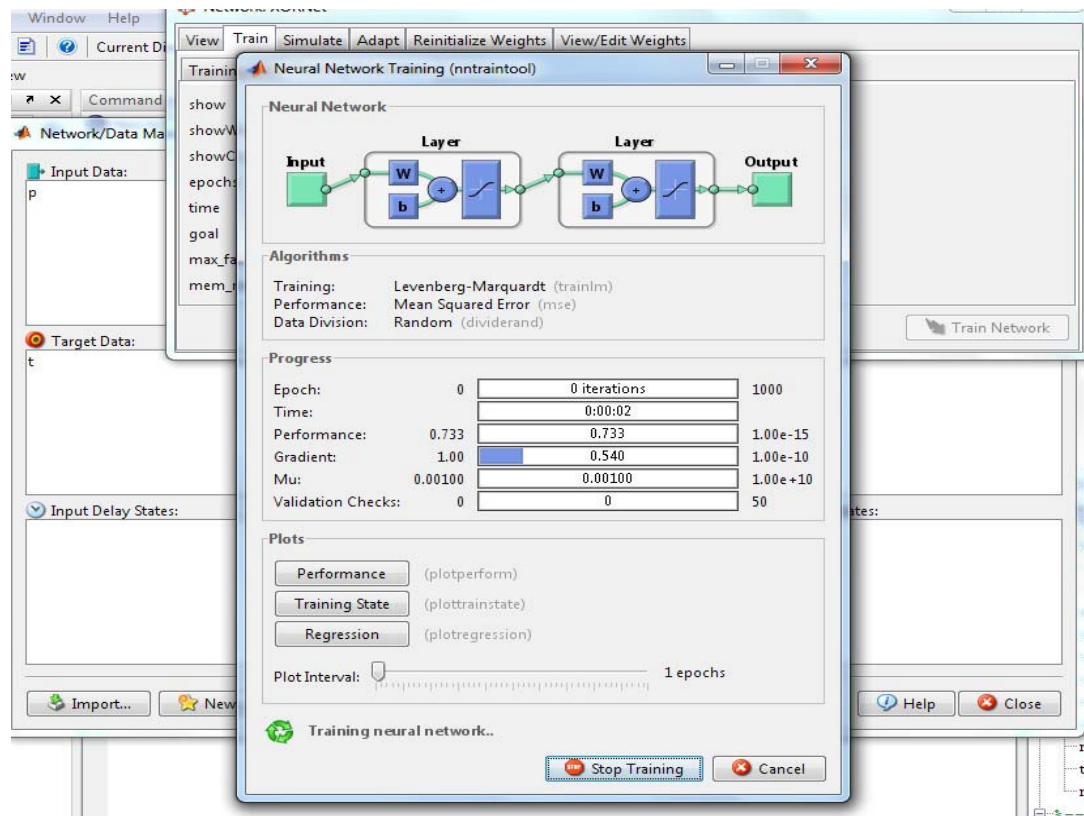


Appendix Figure ANN training in Simulink MATLAB



Appendix Figure ANN training in Simulink MATLAB

THE CAUSE, DEVELOPMENT AND OUTCOME OF WORD-OF-MOUTH MARKETING: WITH PARTICULAR REFERENCE TO WOM VOLUME, VALENCE AND THE MODELING OF VIRAL MARKETING



Appendix Figure ANN training in Simulink MATLAB



## AN INTRODUCTION OF NVIVO

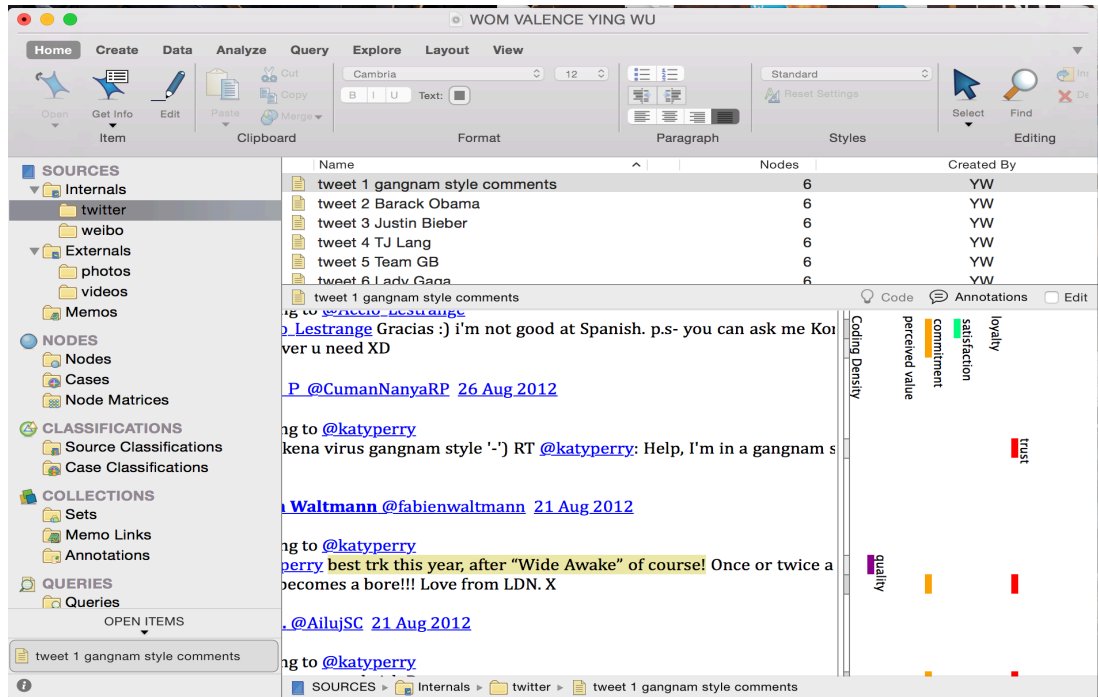
NVivo is software that supports qualitative and mixed methods research. It's designed to help you organize, analyze and find insights in unstructured, or qualitative data like: interviews, open-ended survey responses, articles, social media and web content.

Here are some basic terms in NVivo:

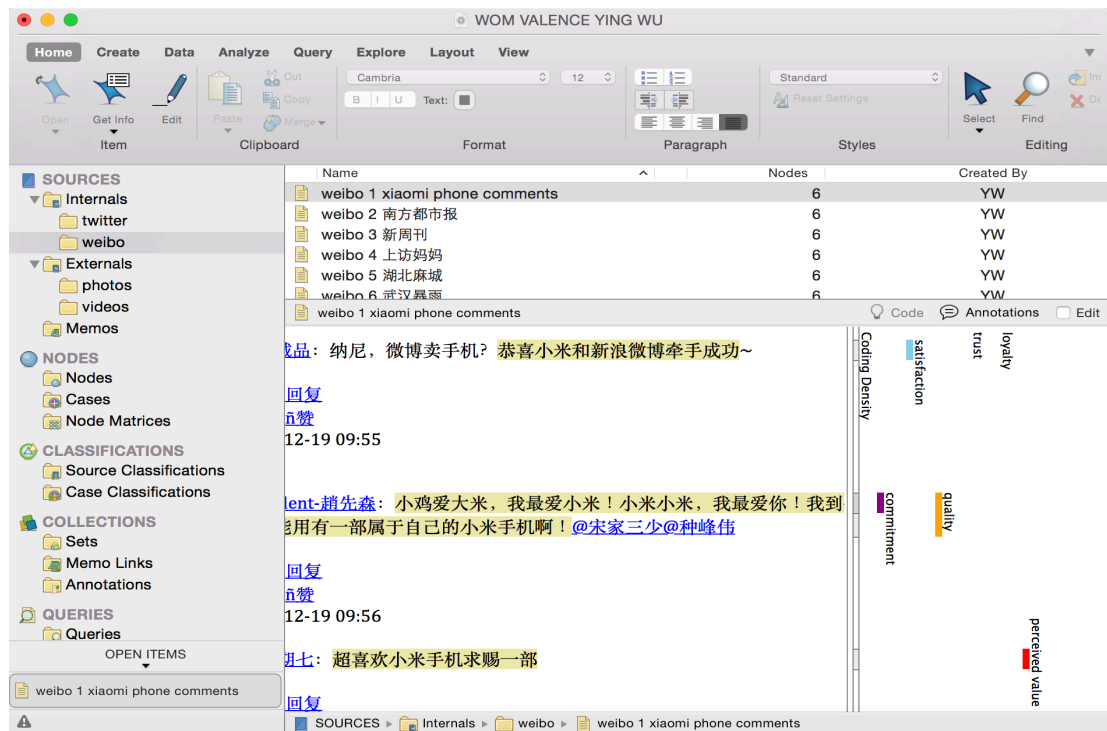
- Sources are the research materials including documents, PDFs, datasets, audio, video, pictures, memos and framework matrices.
- Coding is the process of gathering material by topic, theme or case.
- Nodes are containers for coding
- Source classifications record information about sources
- Node classifications record information about people, places or other cases—for example, user data in social networking sites.

Particularly, a node in NVivo is like a concept or thematic tag. It's possible to create nodes for coding on the fly, or to create node lists in advance – or a combination. It's also possible to create and modify hierarchies of nodes. Sources may be exported with their coding stripes.

## THE CAUSE, DEVELOPMENT AND OUTCOME OF WORD-OF-MOUTH MARKETING: WITH PARTICULAR REFERENCE TO WOM VOLUME, VALENCE AND THE MODELING OF VIRAL MARKETING



Appendix Figure Qualitative data analysis in NVivo (twitter)



Appendix Figure Qualitative data analysis in NVivo (weibo)

## AN INTRODUCTION TO MATLAB AND SIMULINK®

MATLAB is a high-level programming language for mathematics in particular (Barnes and Fulford, 2009). The name MATLAB is short for "MATrix LABoratory". MATLAB was developed in 1970 by the Math Works, Inc., of Natick, Massachusetts; it's for the application involving matrices, linear algebra, and numerical analysis. It's for the application involving matrices, linear algebra, and numerical analysis. The characterizing feature of MATLAB is that it makes dealing with and manipulating matrix both easy and fast. It does not do symbolic algebra, but there is a toolbox available (the symbolic toolbox) which provides the ability to do symbolic algebra..

With the Simulink debugger you can step through a simulation one method at a time and examine the results of executing that method. As the model simulates, you can display information on block states, block inputs and outputs, and block method execution within the Simulink Editor.

- Basically MATLAB is a high-level mathematical programming language that provides mathematical functions and

powerful tools for numerical computation, visualization, and  
application development.

- Simulink® is a powerful instrument in MATLAB for building and managing hierarchical block diagrams and can simplify codes into ready built-in blocks for modeling continuous-time and discrete-time systems.

